Housing Supply, Property Insurance, and Exposure to Wildfire Risk

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Abstract

Over the past decades, about half of new U.S. homes were built in areas exposed to natural hazards. I argue that regulated property-insurance pricing and land-use constraints help explain this pattern. I study San Diego, where wildfire premiums are compressed by regulation and safer locations are tightly constrained. Using detailed spatial data, I estimate a quantitative urban model of household location choice, housing supply, and insurance supply. The results imply substantial underpricing of wildfire risk and large aggregate welfare losses, with important distributional differences. Counterfactuals show that housing-supply reform can substantially reduce the worker burden of cost-based insurance pricing reform.

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I Introduction

As metropolitan populations continue to grow, where cities add housing helps determine who is exposed to climate risk. In the past two decades, about half of new U.S. homes were built in areas exposed to natural hazards (Ospital, 2025). Why has residential development been moving into harm's way even as climate risks intensify? This paper studies whether the answer lies in the within-city geography of housing supply.

This paper argues that two distortions shape this geography. The first is regulated property-insurance pricing that compresses the premium schedule with respect to wildfire risk, weakening the link between local premiums and expected damages. The second is land-use constraints that restrict new housing in safer, high-amenity neighborhoods. Together, these forces push equilibrium sorting toward more hazardous areas.

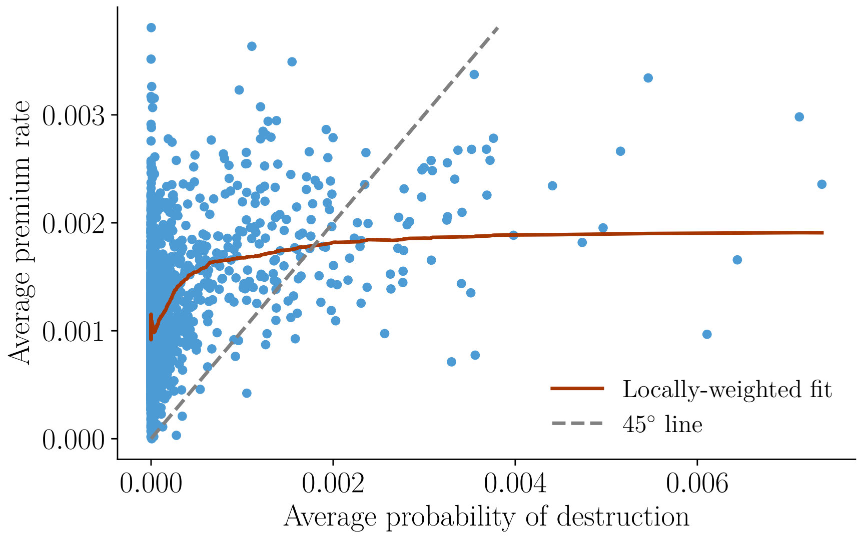
I quantify this mechanism in the San Diego metropolitan area, where wildfire risk rises toward the urban periphery while central neighborhoods are closer to build-out under current regulations. Using granular data on zoning, density limits, wildfire risk, insurance, commuting flows, and parcel-level housing, I estimate a quantitative spatial equilibrium model of household location choices, landowners' housing-supply decisions, and insurance pricing. This allows me to estimate the amenity costs of wildfire risk, the pricing schedule of insurance supply, and to use the model for counterfactual experiments.

In California, property insurance premiums increase less steeply with wildfire risk than expected losses do. Figure 1 illustrates this point by plotting premium rates per dollar of fire coverage against average probability of destruction by a wildfire across California ZIP codes. Under a simple approximation where damages are one-to-one with coverage, this figure shows that high-risk policyholders pay premiums lower than expected losses, and low-risk ones pay more. This pattern, consistent with cross-subsidization of riskier areas by safer ones (Oh et al., 2026), reflects California's institutional setting: regulations limit insurers' use of probabilistic risk models, the FAIR Plan guarantees coverage for high-risk homes, and reinsurance costs are excluded from the premium approval process. These rules compress wildfire premiums relative to expected losses and generate cross-subsidization through the pooled premium for other risks. While the figure offers only coarse evidence, I later show how to use this ZIP-code level data to discipline the magnitude of property damages and the extent of pricing distortions in my model. Moreover, the interpretation is consistent with the property-level results in Boomhower et al. (2024).

San Diego is an ideal stage to study the interaction of building restrictions and wildfire risk. The left-hand panel of Figure 2 shows the distribution of wildfire risk in the study area, with darker shading representing higher risk. Wildfire risk grows eastward as we move from downtown San Diego and the coastline to the urban periphery. About 12% of the San Diego population live in areas with at least 1% probability of a wildfire within the next 30 years, and 7% live in areas with a probability of at least 20% of a wildfire within the same period.[1] The right-hand panel of

[1]Fires spreading from the wildland make the urban periphery of San Diego one of the areas with the highest natural hazard risk in the United States. Wildfires increasingly threaten the health, safety, and comfort of people

Figure 1: Insurance Premiums and Destructive Wildfire Risk Across California ZIP Codes



Notes: Each dot represents a California ZIP code and year tuple. Premium rates per dollar of coverage are calculated using CDI data. Average destruction probabilities are proxied by the housing-unit-weighted average destructive wildfire risk, $\rho_i \equiv \delta_i \times \text{FLEP4}_i$, as measured by the USFS. Here δ_i is burn probability and FLEP4_i is the conditional probability that flame length exceeds 4 feet. Appendix Section B.2 describes the construction in detail.

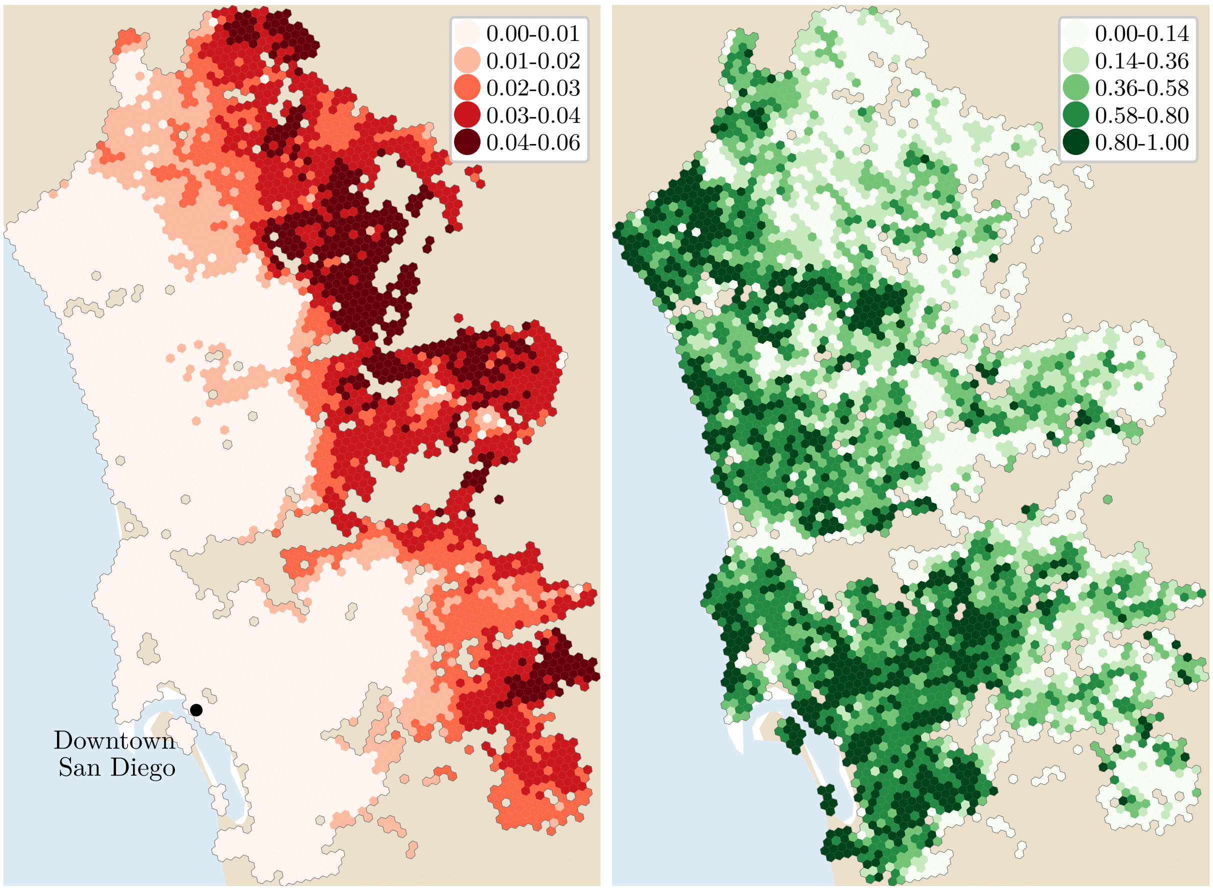
Figure 2 shows housing built as a share of the maximum allowed under current land-use regulations, with darker shading indicating locations closer to capacity. A location is closer to build-out when demand is high or regulations are restrictive. While peripheral areas have ample spare capacity, central areas are closer to build-out. Taken together, the two maps in Figure 2 show that safer areas are also more built out, and, combined with Figure 1, motivate my hypothesis that population exposure to wildfire risk is shaped by the interaction of land-use regulations that constrain housing supply in safer areas and insurance pricing frictions that weaken the price signal in riskier ones.

I develop an urban model where workers choose where to live, potentially being exposed to wildfire risk, and rent housing from landowners who can buy insurance for property damages. As in standard frameworks, workers care about residential amenities, commuting costs, and wage opportunities. Workers also face an amenity cost that captures the expected health and safety consequences of wildfire exposure. I then combine the housing demand system with a housing supply model to solve for the general equilibrium distribution of population, housing, wages, rents, and insurance premiums. I model immobile landowners who choose housing supply subject to expected fire damages and can mitigate those costs by purchasing insurance. On the insurance supply side, I model a regulated wildfire premium schedule together with a pooled premium for

exposed to them. Of the top 20 deadliest wildfires in California's history, 11 have occurred since 2003. Besides the wildfires' direct threat to safety, they have been linked to harmful smoke exposure, deterioration of mental health, and reductions in the value of outdoor recreation. Moreover, wildfire damages to property have dramatically increased in recent years in the United States. Between 2015 and 2018, wildfires caused the same losses, \$53 billion, as in the prior 26 years combined. See Section II.A.2 for citations and data sources.

Figure 2: Wildfire risk and land-use regulations in the San Diego metropolitan area

(a) Annual burn probability (b) Fraction built-out of maximum allowed



Notes: Choropleth maps of wildfire risk and spare building capacity within regular hexagons of side length 560 meters. Annual burn probability is measured by USFS and corresponds to δ_i in Figure 1. Only populated hexagons are shown. The ranges of the bins in each map were chosen following Jenks' classification method.

other perils that adjusts endogenously to satisfy the insurer's self-funding condition. Crucially, I model the land-use regulations observed in the data, which cap the number or size of homes that can be built in each location. These building constraints, when binding, allow landowners to charge higher markups.

To quantify the cost channel of housing supply, I use ZIP-code level data on insurance premiums and coverages for the state of California to estimate the wildfire premium schedule and the magnitude of property damages. Specifically, I estimate the slope of the wildfire premium schedule with average premiums and coverage, and I estimate the damage components that map wildfire and non-wildfire exposure into total premiums. My estimates imply large damages to property: at observed premiums, wildfire insurance accounts for 8.2% of ownership costs on average. At the same time, I estimate significant under-pricing of wildfire risk with premiums 10.5% below actuarially fair pricing and 24.1% below a benchmark equal to actuarially fair pricing plus an 18% risk load.

My estimates also imply substantial cross-subsidization: all else equal, raising wildfire premiums by 10% would reduce the premiums of other perils by 2.27%.

I estimate the remaining parts of the model using highly granular data on wildfire risk, detailed information on land-use regulations, and parcel-level housing values recovered from tax assessment records and 18 years of transaction data. I use a fine spatial grid of regular hexagons with 215-meter sides because wildfire risk varies over short distances and my estimates imply highly localized amenity costs. Tax assessment records provide granular information on housing, but assessed values can differ sharply from market prices because of institutional features of the assessment process. In California, properties are generally reassessed only when they are sold, and otherwise assessed values can rise by at most 2% per year.[2] To recover market-value assessments, I mimic an assessor who combines the most recent sale price with subsequent sales of comparable properties. Specifically, I first use transactions to estimate the time-varying hedonic value of property characteristics. I then use these estimates to impute prices in years without sales by updating the level of the most recent transaction price.

Leveraging the location demand model, I estimate that the residential amenity costs of wildfire risk are large but localized. The model yields a composite amenity that rationalizes observed housing choices and rents, and I identify the wildfire component from very local variation in wildfire risk across nearby places with similar topography and distance to wildland. I find that wildfire risk reduces the amenity value of both a location and nearby areas within a 0.5 km radius. Residents would be willing to pay an equivalent of 5.1% of annual income to avoid a 4% annual probability of wildfire in their own hexagon, the low end of the riskiest bin in Figure 2. Accounting for spatial lags and the joint distribution of risk and residents, these estimates imply an average willingness to pay to remove current risk of 3.5% of income. Instrumental-variable specifications addressing reverse causation from development to wildfire ignitions and omitted amenity differences correlated with climate and topography yield similar or larger estimates, suggesting that the baseline estimates are conservative.

A central aspect of the model's quantification is detailed land-use regulation data, allowing me to estimate the spatial variation in the steepness of housing supply. These regulations are hard to measure because they are complex, take many forms, and can vary considerably between municipalities. To measure these variables at a fine spatial resolution, I extracted the current land-use zoning designation for each parcel and the development regulations from the zoning maps of all jurisdictions in the San Diego area, and combined them with parcel-level data on all lots in the county. These parcel-level rules allow me to recover the housing capacity implied by current regulations in each hexagon and, together with observed housing, to measure how close each location is to build-out. In the model, this build-out rate governs markup elasticity, so locations closer to capacity have steeper inverse supply curves. I then estimate how that elasticity varies across space from differential rent and housing growth across hexagons, allowing the land-use data to

[2]More precisely, the Assessor's Office updates this field in their system when there is a sale of the property; when there is an improvement to the property; when a calamity occurs that reduces the value of the property; or when the annual Proposition 13 valuation changes are applied. These changes match the CPI or 2%, whichever is lower.

discipline the spatial variation in housing supply used in the counterfactuals. The estimated markup elasticities are on average between 1.2 and 1.5 in the safest areas and decline to below 0.2 in the riskiest areas.

I use the estimated model to quantify the welfare cost of wildfire risk and to decompose how insurance pricing and building constraints shape that burden. In the preferred baseline, the welfare cost of wildfire risk is \$17.5 billion in present value. This is the money-metric welfare gain from reducing wildfire probabilities to the 1st percentile value while holding the rest of the policy environment fixed. I can then evaluate the role of the distortions by netting out their direct welfare effects, effectively calculating the differential welfare gain from reducing wildfire risk in the current equilibrium and in one with alternative distributions of building constraints or insurance premium schedules. Aggregate distortion counterfactuals show that the two distortions play different roles: uniformly increasing the sensitivity of wildfire premiums to risk by 10% raises aggregate costs by \$127 million, while uniformly expanding housing capacity by 10% raises it by \$175 million but mainly redistributes incidence away from workers by eroding scarcity gains on safe land. The aggregate interaction between the two distortions is close to zero, indicating that their joint effect mainly reallocates wildfire costs across groups rather than amplifying total costs.

I then study two targeted reforms: up-zoning parcels within a half-mile of major transit stops by 15% and replacing the current cross-subsidized insurance schedule with cost-based premiums, separately and jointly. Cost-based insurance raises the aggregate welfare cost of wildfires by \$460 million. In the benchmark no-amenity specification, targeted up-zoning has a small aggregate effect but lowers worker costs by \$475 million and shifts residents away from the fire-prone fringe. When combined, the two reforms leave the aggregate interaction close to zero but meaningfully reallocate incidence: targeted up-zoning attenuates the worker-side burden of cost-based insurance even as the joint reform increases the burden on owners of risky land. Later robustness exercises show that the aggregate WCW effect of targeted up-zoning is model-dependent, so I interpret this result as a contingent incidence effect rather than a general policy prescription. These counterfactuals highlight a central trade-off: policies that improve the spatial allocation of development relative to wildfire risk can still carry important affordability and distributional consequences.

The main contribution of this paper is to show how granular housing supply policies shape the spatial distribution of exposure to natural hazard risk. It contributes to the literature that uses quantitative spatial models to study climate-risk adaptation (Jia et al., 2022; Balboni, 2021; Desmet et al., 2021; Costinot et al., 2016; Cruz, 2021; Cruz and Rossi-Hansberg, 2021; Nath, 2021; Hsiao, 2025). That work emphasizes reallocation across space as an adaptation margin. I bring this perspective inside a city (like Hsiao, 2025) and add two mechanisms that are central in urban natural hazard risk: granular land-use constraints on safe locations and regulated insurance pricing that endogenously redistributes premium burdens across space. The result is a framework that can separate the housing-supply and insurance channels through which climate risk is capitalized into urban development.

This paper also expands a recent literature on spatial policies that target natural hazard exposure. Recent hazard papers show that spatial regulation can redirect construction and reduce damages in risky places: Ostriker and Russo (2026) study floodplain regulation in Florida, while wildfire papers examine suppression, building codes, housing prices, mortgages, and migration (Baylis and Boomhower, 2019, 2021; Garnache, 2020; Issler et al., 2020; McConnell et al., 2021). Oh et al. (2026) show that regulatory constraints can generate climate-risk cross-subsidies among policyholders in different U.S. states. I complement these efforts by showing how land-use constraints in safer neighborhoods and insurance cross-subsidies in riskier ones jointly determine the spatial distribution and incidence of wildfire risk within a city.

Finally, this paper also contributes to a large urban literature studying how land-use regulation raises housing costs and reshapes the incidence of scarcity (Gyourko and Molloy, 2015; Acosta, 2021; Martynov, 2021; Anagol et al., 2021; Favilukis et al., 2022). Recent work shows that housing supply conditions vary sharply within cities and that departures from perfect competition can matter for how local supply elasticities and housing-policy counterfactuals are interpreted (Baum-Snow and Han, 2024; Watson and Ziv, 2025). I bring that logic to a quantitative spatial equilibrium model with endogenous heterogeneous markups, and estimate spatial variation in markup elasticities using parcel-level capacity data.

II Setting: The San Diego Metropolitan Area

Three features make San Diego a useful setting for this paper: wildfire risk is concentrated on the urban fringe, safer central neighborhoods are more supply constrained, and California insurance premiums rise only weakly with wildfire risk.

II.A Wildfires Threaten the Urban Periphery

This study focuses on the San Diego metropolitan area because it has both high exposure to natural hazard risk and a large dispersion in the degree of risk exposure. The main natural hazard threatening San Diego, as well as most of California, is wildfires. To the east, the metropolitan area borders state and federal parks, areas of rugged terrain and wildland with a landscape dominated by fire-prone native shrubland (Figure A.1 in the appendix shows a detailed map). It is from this wildland that fires can spread to homes in the urban periphery of San Diego.

II.A.1 Exposure to wildfire risk

San Diego County is among the places in the United States with the highest natural hazard risk, both on average and in the dispersion of risk within the county. According to FEMA's NRI index, 95.5% of U.S. counties and 91.3% of counties in California have a lower overall risk. This position in the overall ranking is driven mostly by wildfire risk. San Diego County ranks third in the country in wildfire risk, behind Riverside and Los Angeles County. Moreover, the variance of wildfire risk across census tracts in San Diego-Chula Vista-Carlsbad is a close second among all core-based statistical areas (CBSA) with more than one million people, being surpassed only by the Riverside-San Bernardino-Ontario CBSA. Considering all risks, its variance ranks third after Sacramento-Roseville-Folsom, California, and Houston-The Woodlands-Sugarland, Texas.

In my study area, 358,000 people, or 12% of the population, live in places with at least a 1% cumulative burn probability over 30 years. First Street Foundation uses that threshold to separate places with no or minor wildfire risk from places with moderate or higher risk. It classifies places above a 26% cumulative burn probability over 30 years as "extreme risk," and 139,000 people, or 4.6% of the San Diego metropolitan population, live in such areas. Whether these probabilities are large in welfare terms ultimately depends on damages and risk preferences, which I quantify later.

A natural concern is that human development may itself affect wildfire risk. In principle, the link is non-monotonic: development can increase wildfire risk at low densities through accidental ignitions, but reduce it at high densities through faster detection, greater firefighting effort, or vegetation fragmentation (Andela et al., 2017; Knorr et al., 2016a,b, 2014). That concern is limited in San Diego because the paper studies a highly urbanized metropolitan area, where additional density is unlikely to raise ignitions at the margin, and because the rugged terrain surrounding the city leaves little scope for sprawling land-use changes that would fragment wild vegetation. As mapped in Figure A.2 in the appendix, much of the surrounding terrain is steep, and areas with slopes above 15% are severely constrained for residential construction (Saiz, 2010). Accordingly, I treat wildfire risk as exogenous in the benchmark analysis, but later relax this assumption by estimating how housing density affects burn probabilities and using that relation in robustness exercises with endogenous wildfire risk.

II.A.2 The dangers of wildfires to property, health, and comfort

When a wildfire burns, exposed people and buildings can suffer severe damages. Wildfire exposure creates large property losses and substantial costs to health, safety, comfort, and outdoor recreation, and smoke spreads some of those harms beyond the properties that burn. Wildfire damages to property have increased sharply in recent years. In only four years, from 2015 to 2018, wildfires in the United States caused the same losses, $53 billion, as in the previous 25 years (1990–2014).[3] In California, 14 of the top 20 most destructive wildfires and 9 of the top 20 deadliest wildfires in the state's history occurred since 2017 (CAL FIRE, 2025). This timing matters for the later quantification because I anchor the baseline estimation in 2017, before the recent run of catastrophic California wildfires.

In the model, I capture these consequences through property damages and reductions in residential amenity values. The amenity component is meant to summarize the effects of wildfire exposure on health, safety, smoke, and outdoor recreation (Xu et al., 2020; Burke et al., 2020, 2023; Gellman et al., 2021; Kim and Jakus, 2019; Richardson et al., 2012). The next subsection explains why insurance regulation weakens the extent to which property damages are priced locally.

[3]This is in terms of both insured and uninsured losses, based on Munich Re estimates, transformed to 2015 U.S. dollars using the Consumer Price Index.

II.A.3 Home insurance and risk mitigation

The extent to which the dangers described in the previous section affect the well-being of people (as well as affecting buildings) depends on the opportunities and costs of risk mitigation. In my model I include a key factor that can help mitigate the financial costs of natural hazards: insurance. Wildfires differ from other hazards, such as floods, in that standard homeowner policies typically include coverage against wildfire damage. However, regulatory distortions may lead to cross-subsidization where low risk areas pay high premiums and high risk areas pay low premiums (Oh et al., 2026).

The homeowner insurance market in California has three important institutional features that may lead to cross-subsidization. The first is the mandated existence of an insurer of last resort, the California Fair Access to Insurance Requirements (FAIR) Plan Association, that is financed by all insurance companies operating in California. The FAIR Plan provides a basic policy with limited coverage (including wildfires) to homes that cannot obtain coverage in the standard market.

The second institutional feature is the regulated use of probabilistic models. Insurers in the admitted market are not allowed to use probabilistic models in setting premiums. They can use only their history of losses to support rate change requests. They are allowed, however, to use these tools to decide whether to write or renew a policy. The short available history may not be representative of events that happen only once in 250 years or once in 500 years, which could lead to both underpricing of the real risk and overpricing of regions where an event happens.[4]

The third feature is the disallowance of reinsurance costs in rate change requests. That is, the regulator prohibits insurers from incorporating reinsurance costs in rate schedules when requesting permission to update premiums. This incentivizes insurance companies to reduce the number of high-risk properties insured. However, that margin of adjustment is limited by moratoria in policy cancellations in the wake of wildfire events.

Figure 1 shows evidence that California ZIP codes with high risk pay premiums lower than expected losses, and low risk ones pay more. The figure shows a scatter plot of the average premium per dollar of fire coverage obtained from the California Department of Insurance (CDI) against the probability of destruction constructed using burn probabilities from the USFS. The solid curve, a locally-weighted regression fit, shows that the relationship is concave and that low-risk areas pay premiums above their expected losses (above the 45-degree line) while the riskiest areas pay premiums below expected losses (below the 45-degree line). While this data is coarse and does not account for potentially important sources of heterogeneity between ZIP codes, the premium schedule is consistent with the results in Boomhower et al. (2024) which rely on property-level cost estimates and premiums. Moreover, the concavity survives adding controls.[5]

[4]The regulator has criticized the risk models for their omission of some inputs (e.g., mitigation efforts), and raised the concern that the modeled risk scores produced are not granular enough for use on particular properties (Cignarale et al., 2017).

[5]Specifically, including controls for mortgage share, seasonal homes share, vacant share, and median built year in a regression of premiums per $1,000 of coverage on expected losses and expected losses squared results in a coefficient of 0.276 and -0.021.

There are other forms of risk mitigation, both private and carried out by governments, that do not appear explicitly in my analysis. Although I implicitly include them in my measurements and estimates of risk and damages, they remain fixed by assumption in the counterfactual experiments. Private mitigation methods include expenses paid by homeowners to protect their properties, such as the elimination of flammable materials inside a "defensible space" around a home, or the use of ignition-resistant roofing (Baylis and Boomhower, 2021). Another example is air filtration technology. Survey evidence shows that a majority of people exposed to wildfire smoke from California's Station Fire of 2009 ran the air conditioner more than usual (Richardson et al., 2012).

A notable way to mitigate wildfire risk is through suppression. The federal government and the state of California are in charge of suppressing the majority of fires because they start in land that these institutions own, and these expenditures have been growing over time. I chose to treat government suppression as given because looking at data from incident reports I found that the per capita cost of firefighting in the parks around the study area is small. Moreover, a recent paper, Baylis and Boomhower (2019), estimates the per-home implicit subsidy of federal firefighting and finds that the expected protection costs are low in Southern California. The reason is that firefighting costs are non-monotonic in density: beyond low levels of housing density, the marginal effect of additional homes on firefighting expenditures is small.

II.B Land-use Regulations

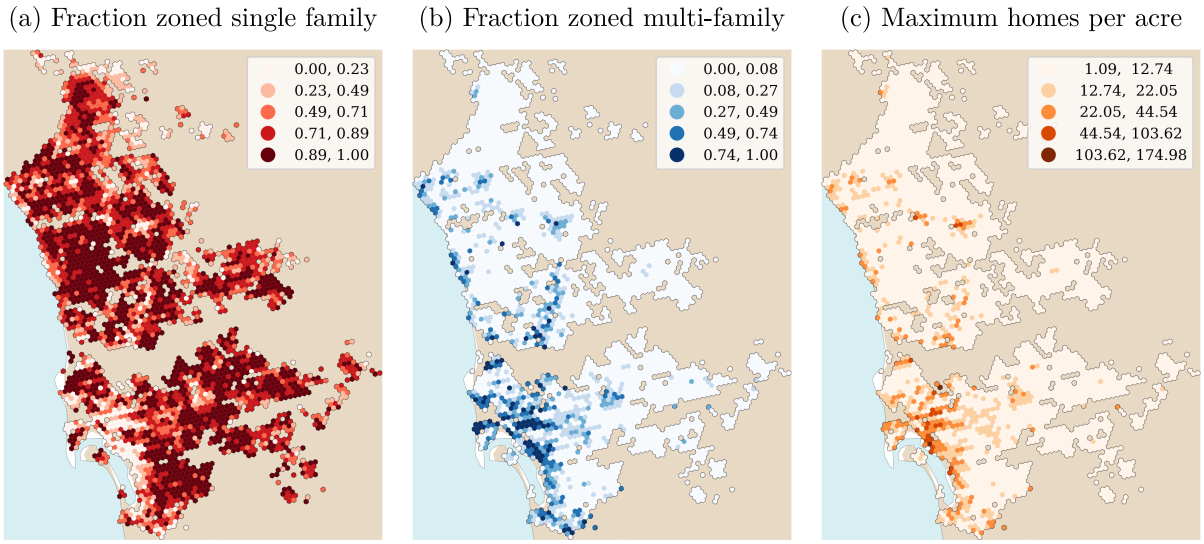
Strict land-use regulations in areas with high demand, such as San Diego, are credited with deteriorating housing affordability. The maps in Figure 2 suggest that this pattern is also present within cities, and that central areas tend to have higher demand and be closer to regulatory build-out.

California house prices and rents are at historic highs and housing production is at historic lows. San Diego is not an exception: median house values increased from 2.7 to 6.9 times the median income between 1970 and 2017, and median rents increased from 16.3% to 24% of median income in the same period (LTDB, 2010). The region added an average of about 25,000 homes annually in the 1970s and 1980s but fewer than 7,000 homes per year since 2006 (SANDAG, 2019).

Restrictive land-use regulations are widely credited with originating the housing supply shortage (Molnar, 2022). Panels (a) and (b) of Figure 3 show the distribution of single- and multi-family zoning over a 560-meter-sided hexagonal grid, with a darker color indicating a larger fraction of a hexagon is zoned that way. In the San Diego metropolitan area, more than 80% of the residential land is reserved exclusively for low-density detached single-family homes. The multi-family zones are mostly concentrated close to Downtown San Diego and along the coastline.

Panel (c) plots the maximum number of homes (i.e., dwelling units) allowed per acre of land. The vast majority of the residential land is mandated to be under 12 dwelling units per acre, and these are typically single-family detached homes. Densities between 12 and 30 dwelling units per acre are typically achieved by duplexes or row houses. The areas that allow the most density are close to Downtown San Diego and along the coast. However, high-density areas are very limited,

Figure 3: Zoning and maximum homes allowed



Notes: Choropleth maps of zoning and maximum density allowed within regular hexagons of side length 560 meters. Only populated hexagons are shown. Data from municipal codes and zoning maps of cities in San Diego County and the San Diego Association of Governments. Refer to Section B for details on data collection.

and even the densest are relatively sparse. Densities between 100 and 150 dwelling units per acre, similar to the higher bin in the map, are typically achieved with 5–7-story apartment buildings with underground parking.

III Model

The model links household location choice, constrained housing supply, and regulated insurance pricing to the spatial incidence of wildfire risk within the city. Wildfire risk lowers residential amenities for workers and raises expected costs for landowners, while building constraints amplify the resulting spatial differences in rents and development.

I first develop a model of location choice within the city. I will later leverage the model's structure to estimate the reduction in residential amenity values associated with wildfire risk. These amenity costs capture all the negative outcomes related to health, safety, and comfort that arise from being close to a burning wildfire, as described in II.A.2.

Second, I combine the previous housing demand system with a housing supply model to determine a spatial equilibrium. The supply side captures the effect of property damages, as well as the role of property insurance markets in mitigating those losses. Moreover, building constraints affect the curvature of housing supply through an increase in markups.[6]

[6] One could instead model building constraints as affecting curvature through marginal costs, but this would imply different effects on landowner welfare. Moreover, in a low-density setting like San Diego, it seems more plausible that convexity arises from demand rather than costs, as might be the case in a dense environment such as New York City (Rollet, 2025).

III.A Location Choice with Wildfire Risk

Workers choose where to live and work. In making these decisions they weigh the expected amenity costs of wildfire risk and the value of other residential amenities against housing costs, and weigh wages against commuting costs.

The model partitions the San Diego metropolitan area into two geographic levels. The upper level is census tracts. Each tract is then partitioned into residential locations, which are a grid of 215-meter-sided regular hexagons. I use capital letters I and J to indicate the tracts, and lowercase letters i and r to indicate the hexagons. The notation $I(i)$ indicates the tract where hexagon i is located. I use this fine resolution because wildfire risk varies over very short distances. The two levels differ in spatial resolution, which allows me to keep the model computationally tractable while still modeling commuting choices—a key determinant of location values and realistic substitution patterns.

There is a continuum of workers indexed by ι who first draw idiosyncratic values $z^{city}(\iota)$ and $z^{out}(\iota)$ for living in the modeled city (the San Diego Metropolitan Area) or in the rest of the country, and choose one of the two options. Second, they draw idiosyncratic values for residential hexagons $b_i(\iota)$ and choose one to live in. Third, they draw idiosyncratic labor productivities $e_J(\iota)$ for each workplace tract in the city, and choose one as their commuting destination. I assume that the idiosyncratic values $z^{city}(\iota)$, $z^{out}(\iota)$, $b_i(\iota)$ and $e_J(\iota)$ are i.i.d. type II extreme value with shape parameters $\varepsilon^C > 1$, $\varepsilon > 1$ and $\theta > 1$ and means equal to 1.

To live in hexagon i, workers need to rent a home there and they choose one among those offered by landowners indexed by $\ell \in (0,1)$. They have heterogeneous preferences over homes captured by $\epsilon(\ell,\iota)$, which they draw from an i.i.d. Gumbel distribution. Workers pay for rent with the income from a unit of labor supplied inelastically in their workplace tract, and spend the remaining income on a consumption good that is freely traded nationally. Wildfires happen after workers make all these choices except the consumption of the tradable good.

The value of home ℓ to worker ι is given by $\ln \omega_i(\ell) + (1-\zeta)\ln q_i(\ell) + \epsilon(\ell,\iota)$, where $\omega_i(\ell)$ is a preference shifter common across workers, $\zeta > 1$ is a parameter, and $q_i(\ell)$ is the rent price of home ℓ. Given the distributional assumption on the idiosyncratic values $\epsilon(\ell,\iota)$, the demand for housing space takes the form

$$h_i(\ell) = \omega_i(\ell)\frac{H_i}{L_i}\left(\frac{q_i(\ell)}{Q_i}\right)^{-\zeta}, \tag{1}$$

where $Q_i \equiv \left(\int_0^1 \omega_i(\ell)\,(q_i(\ell))^{1-\zeta}\,d\ell\right)^{1/(1-\zeta)}$ is the price index. The corresponding aggregate housing demand in hexagon i is then $H_i = L_i\left(\int_0^1 (\omega_i(\ell))^{1/\zeta}\,(h_i(\ell))^{1-1/\zeta}\,d\ell\right)^{\zeta/(\zeta-1)}$.

I assume Cobb-Douglas utility between the consumption good and housing, with expenditure shares β and $1-\beta$. If Q_i denotes rents and B_i the residential appeal (i.e., amenity value), the distributional assumptions on the idiosyncratic values imply that the probability that a worker chooses to live in i is

$$\lambda_i \quad = \quad \frac{\left(B_i \mathbb{W}_i Q_i^{\beta-1}\right)^{\varepsilon}}{\sum_{i'} \left(B_{i'} \mathbb{W}_{i'} Q_{i'}^{\beta-1}\right)^{\varepsilon}}. \tag{2}$$

The variable $\mathbb{W}_i$ is maximized expected income, and thus incorporates the value of the optimally chosen workplace and depends on commuting costs and the value of the shape parameter θ.

Workers first choose whether to live in the city or in the rest of the country. The rest of the country is the outside option and offers mean utility $\mathcal{U}$. From the residential choice, the expected utility of living in the city is $\mathcal{V} = \left[\sum_i \left(B_i \mathbb{W}_i Q_i^{\beta-1}\right)^{\varepsilon}\right]^{1/\varepsilon}$. Under these assumptions, the probability of choosing to live in the city is

$$\lambda^C = \frac{\mathcal{V}^{\varepsilon^C}}{\mathcal{U}^{\varepsilon^C} + \mathcal{V}^{\varepsilon^C}}. \tag{3}$$

The total number of workers in the country is exogenous and given by N^*. Therefore, the city population is $N = \lambda^C N^*$ and the population in a hexagon is $N_i = \lambda_i N$. Workers' housing expenditures in hexagon i are then

$$Q_i H_i = (1 - \beta)\, \mathbb{W}_i N_i. \tag{4}$$

I distinguish between two wildfire-risk objects. For workers, the relevant object is the annual burn probability δ_i, because even manageable fires can reduce residential amenity through smoke, evacuation risk, disruption, and perceived danger. For property damages and insurance, the relevant object is destructive wildfire risk, $\rho_i \equiv \delta_i \times \text{FLEP4}_i$, where FLEP4_i is the conditional probability that flame length exceeds 4 feet. I parametrize the amenity damages of wildfire risk exposure using δ_i, and later estimate these parameters.

I assume there is a constant marginal willingness to pay for a reduction in wildfire risk, expressed as a fraction of income, equal to φ^B. That assumption implies $B_i \propto \exp\left(-\varphi^B \delta_i\right)$. I also let amenities vary endogenously depending on the average income, $\mathbb{W}_I$ and the population density N_I / L_I in the tract, where $L_I \equiv \sum_{i \in I} L_i$ is the tract's total residential land. This allows, in a reduced form, for the possibility of variety effects in retail amenities, congestion effects or direct preferences for density, or locally-funded public goods. Specifically, I assume that amenities are

$$B_i = b_i e^{-\varphi^B \delta_i} \left(\mathbb{W}_{I(i)}\right)^{\eta^W} \left(\frac{N_{I(i)}}{L_{I(i)}}\right)^{-\eta^N}, \tag{5}$$

where b_i is an exogenous fundamental amenity level, the parameter η^W is the elasticity of amenity value with respect to average income, and the parameter η^N is the elasticity of amenity value with respect to population density.

III.B Housing Supply with Wildfire Risk and Insurance

Landowners choose housing supply under wildfire damage risk and regulated insurance pricing. These forces make local development costs depend on burn risk and make the slope of local supply depend on how close development is to regulatory capacity.

In each hexagon i there is a unit-mass continuum of landowners, indexed by $\ell \in (0,1)$, that represents the distribution of lots across the stock of land zoned for housing, L_i. Thus, integrals over ℓ are lot-level averages, and multiplying those averages by L_i yields the corresponding hexagon-level totals. Each landowner controls one lot, chooses how much housing space $h_i(\ell)$ to build on it under conditions of monopolistic competition, and then rents it to workers at price $q_i(\ell)$. After building housing, landowners can purchase insurance coverage for wildfire and other damages. After the realization of property damages, landowners use their remaining rental profits for consumption of the tradable good. I assume they have preferences with constant absolute risk aversion (i.e., invariance of risk aversion across the wealth distribution), characterized by utility function $U(C) = 1 - \exp(-\sigma C)$, where $\sigma > 0$ is the coefficient of absolute risk aversion.

Insurable property damage is either wildfire-related or non-wildfire-related. With probability ρ_i, a destructive wildfire occurs and the landowner incurs wildfire damages $\varphi_i^H h_i(\ell)$, which scale with the housing stock $h_i(\ell)$. Non-wildfire damages equal φ^o per unit of housing and occur independently with probability ρ^o. These represent perils such as plumbing failures, theft, hail, and small structure fires that can affect any house in the city, including locations far from the wildland interface. Landowners purchase insurance coverage x_i and x_i^o at prices p_i and p^o to offset wildfire and non-wildfire losses, respectively.

Landowners within a location i are uniform with the exception of the demand shifter $\omega_i(\ell)$, which implies that housing space in different lots is only imperfectly substitutable from the perspective of renters. I assume that these demand shocks are drawn independently and identically (i.i.d.) from distribution G with unit mean and finite variance. All landowners in i can supply housing space at a constant development cost d_i, but they are constrained to a maximum allowed per-lot capacity of $\bar{h}_i$.

Starting from the second step, the insurance decision solves the problem of maximizing expected utility subject to the budget constraint while taking the housing space decision as given. The first-order conditions with respect to x_i and x_i^o yield the demands for insurance coverage:

$$x_i = \varphi^H h + \frac{1}{\sigma} \ln\left(\frac{\rho_i}{1-\rho_i} \frac{1-p_i}{p_i}\right), \tag{6}$$

$$x_i^o = \varphi^o h + \frac{1}{\sigma} \ln\left(\frac{\rho^o}{1-\rho^o} \frac{1-p^o}{p^o}\right). \tag{7}$$

Equations 6 and 7 can be interpreted as explaining deviations from full insurance as a function of imperfections in insurance markets. These imperfections will drive a wedge between premiums (p) and expected damages (ρ). If these imperfections cause premiums to exceed expected damages, $p > \rho$, then the second term is negative and it leads to partial insurance. The degree of risk aversion, captured by the coefficient of absolute risk aversion σ, is inversely related to the importance of these distortions. In the extreme, if $\sigma \to \infty$, the landowner always insures fully.

In the first step, landowners decide how much space to build on their land and how much rent to charge. I formalize this choice as landowners maximizing their certainty-equivalent profits subject to the building capacity constraint $h \leq \bar{h}_i$. The constant absolute risk aversion (CARA) assumption means that the profits in the four states of the world are equal in every term that is a function of h and q, so we can focus on the profit maximization problem. The landowner's profit maximization problem is

$$\max_{q_i(\ell),h_i(\ell)} \left[q_i(\ell) - d_i - p_i\varphi^H - p^o\varphi^o\right] h_i(\ell) \qquad \text{subject to} \qquad h_i(\ell) \leq \bar{h}_i \tag{8}$$

and subject to the demand function as given by Equation (1).

The problem in (8) captures that wildfire damages enter as an additional marginal cost in the housing supply decision. Notice, however, that the degree of risk aversion does not affect housing supply or rents; property damages affect housing supply through the insurance premiums p^o and p_i and the marginal damages φ^H and φ^o. This fact is a consequence of the CARA assumption.

Within a location i, landowners only differ in the demand shifter for their home $\omega_i(\ell)$. Therefore we can define a threshold demand at which landowners become constrained $\bar{\omega}_i$. For landowners with less desirable lots $\omega_i(\ell) < \bar{\omega}_i$ the building constraint does not bind, and for landowners with more desirable lots $\omega_i(\ell) \geq \bar{\omega}_i$ the building constraint binds. Solving for $\bar{\omega}_i$ from the first order conditions of the profit maximization problem (8), and replacing the optimal rents into the price index Q_i yields an inverse supply curve:

$$Q_i = \mathcal{M}(\bar{\omega}_i)\, D_i,$$

where $D_i \equiv d_i + p_i\varphi^H + p^o\varphi^o$ is the effective per-unit development cost including insurance and $\mathcal{M}(\bar{\omega}_i)$ is the markup. The markup is only a function of the threshold $\bar{\omega}_i$ and is determined by parameter ζ and the distribution G. It is greater than one ($\mathcal{M} \geq \zeta/(\zeta-1) > 1$) and strictly decreasing ($\mathcal{M}' < 0$). As we approach a situation where no landowners are constrained, $\bar{\omega} \to \infty$, the markup approaches the unrestricted monopolistic competition markup $\zeta/(\zeta-1)$.

Replacing the solution for the threshold $\bar{\omega}_i$ and the optimal rents (8) into the aggregate housing space demand H_i yields $H_i = \bar{h}_i\,\mathcal{H}(\bar{\omega}_i)\,L_i$. The function $\mathcal{H}$ is strictly increasing and known given ζ and G. The total housing capacity in i is $\bar{H}_i \equiv \lim_{\bar{\omega}_i \to 0} H_i(\bar{\omega}_i) \propto \bar{h}_i L_i$, which implies that the buildup rate $H_i/\bar{H}_i$ is just a function of $\bar{\omega}_i$. Moreover, the buildup rate inherits the properties of function $\mathcal{H}$, so it is also strictly decreasing in the threshold $\bar{\omega}_i$. Crucially, that means there is a one-to-one mapping between the cutoff $\bar{\omega}_i$ and the buildup rate $H_i/\bar{H}_i$, which allows us to re-write the inverse supply curve as

$$Q_i = \mathcal{M}(H_i/\bar{H}_i)\, D_i. \tag{9}$$

With very low buildup, $H_i/\bar{H}_i \to 0$, the markup approaches the unrestricted monopolistic competition markup $\zeta/(\zeta-1)$. When we approach full building capacity, $H_i/\bar{H}_i \to 1$, the markup becomes arbitrarily large.

III.C Insurance Supply

There is a regulated insurer that sells coverage to landowners in the city before property damages are realized, and finances payouts using premium revenue.

Regulation constrains the insurer's wildfire premium rate in hexagon i to follow a schedule $p_i = p(\rho_i;\tau)$ parametrized by τ. We impose $p(0;\tau) = 0$, so $p(\rho_i;\tau)$ captures the incremental premium allowed for destructive wildfire risk in a hexagon with probability ρ_i. The shape of this schedule captures regulatory frictions to insurance pricing, such as limits in insurers' use of probabilistic risk models, the FAIR Plan mandated provision of coverage to high-risk homes, and exclusion of reinsurance expenses in the rate-setting process.

In addition, the insurer is subject to a "revenue requirement" that caps total revenues at a constant proportion R of expected costs. The revenue requirement implies the citywide self-funding condition

$$\sum_i \left(p_i x_i + p^o x_i^o\right) L_i = R \sum_i \left(\rho_i x_i + \rho^o x_i^o\right) L_i.$$

The left-hand side is total premium revenue. The right-hand side is expected payouts for a risk-neutral insurer, scaled by R, where $R-1$ can be interpreted as an allowed return, surplus requirement, or risk load.[7]

Since the wildfire premium schedule $p_i = p(\rho_i;\tau)$ is given by regulation, the self-funding condition determines the premium rate for non-wildfire damages endogenously as a function of the spatial distribution of insurance coverage:

$$p^o = R\rho^o - \frac{\sum_i \left(p_i - R\rho_i\right) x_i L_i}{\sum_i x_i^o L_i}. \tag{10}$$

The decomposition in Equation 10 clarifies incidence across perils. When wildfire premiums are "low" relative to expected wildfire costs (adjusted by the revenue requirement), the gap must be closed by a higher pooled premium p^o, raising premiums even in relatively wildfire-safe areas. In particular, if the wildfire pool is exactly self-funded, $p_i = R\rho_i$, the second term equals zero and the non-wildfire premium is actuarially fair up to the risk load $p^o = R\rho^o$. If instead the wildfire pool is under-funded, the numerator of the second term is negative and we obtain that the non-wildfire pool cross-subsidizes wildfire risk: $p^o > R\rho^o$.

III.D Spatial Equilibrium

I now define a spatial equilibrium of the model. I first do this in levels, and then describe my approach to implementing the equilibrium conditions in changes. The version in changes is then the one I used for estimation and simulations. For the sake of expositional clarity I treat wages W_I and expected income $\mathbb{W}_i$ as exogenous, but the version of the model I use, presented in detail in the Appendix, has downward-sloping labor demands across tracts.

Equilibrium. An equilibrium of the model is defined as the set of endogenous variables $\{\lambda_i\}, \lambda^C, \{Q_i\}$ (residential shares, city size, and rents) that given the fundamentals $\{b_i\}$, $\{\mathbb{W}_i\}$, $\mathcal{U}$, $\{d_i\}$, $\left\{\bar{H}_i\right\}$, and N^* satisfy that: the choices of residential hexagons are optimal (2) and a function of amenities as given by Equation 5; city choice is optimal (3); rents equalize demand (4) and supply (9) of housing; and the insurance premium schedule (p^o, p_i) is given by $p_i = p(\rho_i;\tau)$

[7] If instead of modeling the self-funding condition we take the parameters in the premium schedule (p^o, τ) as exogenous, we are implicitly allowing for under or over funding of the modeled city's insurance, depending on whether expected payments are over or under total premiums collected. Such an assumption can be justified by insurance companies (or a state or federal government) cross-subsidizing across regions and states.

and the self-funding condition (10).

Equilibrium in changes. I characterize the equilibrium of the model in changes. For any variable a in an initial equilibrium and a' in a new equilibrium, define $\Delta \ln a \equiv \ln a' - \ln a$. Expressing the equilibrium in changes is straightforward for most conditions, so I relegate those to the Appendix. The main exceptions are changes in housing supply, housing development costs, and insurance premiums. I discuss these in turn below.

The inverse housing supply equation (9) is non-linear in housing through the changes in markups. To improve tractability, I follow the approach in Boehm and Pandalai-Nayar (2022) and replace the changes in markups with a first order approximation around the buildup rate in the initial equilibrium. This yields the following empirical supply curve:

$$\Delta \ln Q_i = \mu_i \left(\Delta \ln H_i - \Delta \ln \bar{H}_i\right) + \Delta \ln D_i, \tag{11}$$

where $\mu_i \equiv \mu(H_i/\bar{H}_i) > 0$ is the markup elasticity.

Equation 11 provides a micro-foundation for heterogeneous housing supply elasticities (μ_i^{-1}) across locations in the city, arising endogenously from differences in housing already built (H_i) relative to building capacity ($\bar{H}_i$). The supply curve is convex when the markup elasticity is increasing in buildup: $\mu' > 0$. That means that an increase in housing demand ($\Delta \ln H_i$) will lead to larger price increases in locations built closer to capacity, and that an increase in capacity ($\Delta \ln \bar{H}_i$) due to, for example, an up-zoning policy will decrease prices more in locations where the baseline buildup rate is higher.

The intuition for the convexity of the aggregated supply curve is straightforward. The shape of the curve follows from the assumptions that there are building constraints, so the maximum housing that can be built in each lot is fixed; and that lots are imperfectly substitutable. These imply that increasing the total housing stock in a location necessitates substitution towards less desirable lots, which are not built to capacity. This raises the location's price index. For landowners that are constrained, imperfect substitution allows them to charge markups, which increase with demand if the building constraint binds.

To compute changes in housing development costs D_i, I assume that the wildfire premium schedule is linear in destruction probabilities: $p_i = \tau \rho_i$. Under this assumption, development costs change according to

$$\Delta \ln D_i = \ln \left(1 + \frac{\varphi^H \tau \rho_i}{D_i} \frac{\Delta p_i}{p_i} + \frac{\varphi^o p^o}{D_i} \frac{\Delta p^o}{p^o}\right), \tag{12}$$

where $D_i = d_i + \varphi^H \tau \rho_i + \varphi^o p^o$. This expression maps changes in wildfire premiums p_i and non-wildfire premiums p^o to changes in development costs. The premium changes are weighed by their shares in total unit costs: $\varphi^H p_i / D_i$ and $\varphi^o p^o / D_i$.

In the expression above, the change in non-wildfire premiums is endogenous. I compute $\Delta \ln p^o$ using a first order approximation of the self-funding condition (10). Specifically,

$$\Delta \ln p_o = \varpi^o \sum_i \varpi_i \left(\frac{R - \tau}{\tau} \left(\Delta \ln \rho_i + \Delta \ln H_i\right) - \Delta \ln \tau\right), \tag{13}$$

where ϖ^o and ϖ_i are functions of the baseline distribution of total premiums. In particular, $\varpi_i \equiv p_i x_i L_i / (\sum_{i'} p_{i'} x_{i'} L_{i'})$ is the share of total wildfire-related premiums accounted for by location i, and $\varpi^o \equiv (\sum_i p_i x_i L_i)/(\sum_i p^o x_i^o L_i)$ measures the importance of total wildfire-related premiums relative to total premiums for other risks. In deriving this expression, I also approximate changes in coverage by changes in housing space, $\Delta \ln x_i \approx \Delta \ln H_i$.

III.E Theoretical Implications: Determinants of Exposure

Before moving on to quantifying the full model in the next section, here I derive a set of comparative statics that highlight the main economic forces at play in the model.

The model illustrates how differences in housing supply, amenity costs of wildfire risk, property damages, and insurance market distortions all interact in shaping exposure to natural hazard risk within the city. For expositional clarity, in this subsection I abstract away from city choice and assume that there is no migration in or out of the city. I also assume no congestion or external economies of density ($\eta^W = \eta^N = 0$), exogenous wages, and exogenous non-wildfire premiums. I present the key equations here, and leave further details to appendix Section D.

Heterogeneous growth. If we consider marginal changes in the size of the city N and the distribution of population across locations N_i that satisfy the equilibrium conditions we obtain:

$$\frac{d \ln N_i}{d \ln N} = \frac{1}{1 + \varepsilon \left(1 - \beta\right) \frac{\mu_i}{1+\mu_i}}.$$

This expression shows the equilibrium distribution of local populations that results from increasing the total population of the city. Crucially, growth is heterogeneous across locations because of differences in markup elasticities, μ_i, and this growth is decreasing in μ_i:

$$\frac{\partial}{\partial \mu_i}\left(\frac{d \ln N_i}{d \ln N}\right) < 0.$$

This result is intuitive: places with higher μ_i (steeper supply) expand less when the overall city grows.

Determinants of risk exposure. If we now consider marginal changes in burn probabilities and the distribution of population across locations that satisfy the equilibrium conditions we obtain an expression for the determinants of risk exposure:

$$\underbrace{\frac{d \ln N_i}{d\delta_i}}_{\text{Exposure}} \;=\; \varepsilon \underbrace{\frac{1}{1 + \varepsilon \left(1 - \beta\right) \frac{\mu_i}{1+\mu_i}}}_{\text{Supply damping}} \left(\underbrace{\frac{d \ln B_i}{d\delta_i}}_{\text{Amenity channel}} - \underbrace{\frac{1-\beta}{1+\mu_i}\frac{d \ln D_i}{d\delta_i}}_{\text{Property channel}} \right).$$

This expression is a local within-city comparative static evaluated holding total city population fixed ($d \ln N = 0$). The population-risk gradient at location i, $d \ln N_i / d\delta_i$, is driven by two channels: changes in amenities and changes in property costs. The prefactor $\left[1 + \varepsilon(1-\beta)\frac{\mu_i}{1+\mu_i}\right]^{-1}$ captures how local housing supply shapes the response to either channel. Because this term is decreasing in μ_i, steeper local housing supply dampens the absolute response of local population to a marginal change in wildfire risk.

To gain further insight, we can replace the amenity with the assumed functional form (equation

5) and the development productivity with the expression resulting from the micro-foundation of insurance demand ($D_i \equiv d_i + p_i\varphi^H + p^o\varphi^o$). Replacing, we obtain

$$\frac{d\ln N_i}{d\delta_i} = \varepsilon\frac{1}{1+\varepsilon\left(1-\beta\right)\frac{\mu_i}{1+\mu_i}}\left[-\underbrace{\varphi^B}_{\text{Amenity}} - \left(1-\beta\right)\frac{1}{1+\mu_i}\frac{\overbrace{\varphi^H}^{\text{Damages}}}{D_i}\underbrace{\frac{dp_i}{d\delta_i}}_{\text{Insurance}}\right].$$

Recall that the parameter $\varphi^B > 0$ captures the amenity costs of risk exposure, while the parameter $\varphi^H > 0$ captures property damages and p_i are insurance premiums. Because insurer-side risk is $\rho_i = \delta_i \times \text{FLEP4}_i$, the derivative $dp_i/d\delta_i$ should be interpreted as the premium response to a marginal increase in burn probability holding local fire intensity fixed.

Naturally, exposure is lower when the amenity costs of exposure (φ^B) are higher, as people would want to avoid those locations. The property cost channel is determined by the magnitude of damages, φ^H/D_i, and by the sign and magnitude of the insurance price gradient, $dp_i/d\delta_i$. Insurance reduces exposure if premiums are increasing in risk ($dp_i/d\delta_i > 0$), but if cross-subsidization is strong enough that premiums increase only weakly with risk or even fall with risk, then the property cost channel is weaker or can even offset the amenity channel.

Local housing supply affects this response in two ways. A higher μ_i attenuates the overall population response through the common prefactor, and it further attenuates the property cost channel through the factor $1/\left(1+\mu_i\right)$. Equivalently, steeper local housing supply weakens sorting away from marginal increases in wildfire risk. This is a local within-city force; quantifying the full model is therefore essential to determine how it combines in equilibrium with cross-location differences in supply, amenity costs, damages, and insurance pricing.

IV Quantification

I quantify the model by separately estimating household demand, local supply elasticities, and insurance-pricing and damage parameters using San Diego and California data.

To estimate the parameters governing worker preferences and housing supply curves I use data for the exact hexagonal geographies within the San Diego Metropolitan area where I then run the simulations. Below, I present separate regressions because it makes transparent the sources of variation identifying each parameter. But I also bootstrap the full estimation procedure to capture joint estimation uncertainty. I refer to these confidence intervals when discussing the parameter values implied by the regressions, and they are all collected in Table A.1.

Some additional parameters require estimation external to the model. To estimate property damages and insurance supply parameters I assemble a ZIP-code level panel dataset for the whole of California. To estimate the relationships between temperature, housing density, and wildfire risk, which I use in robustness exercises and extensions, I construct a California panel at a lower-resolution hexagonal level.

IV.A Data on Housing, Population, and Wildfire Risk in the San Diego Area

I quantify the model with detailed data on commuting flows, the distribution of homes in space, and probabilistic measures of wildfire risk. I adjust all nominal monetary variables described next to 2018 dollars using the California Consumer Price Index from the Department of Industrial Relations.

Geographic units. Throughout the analysis I use data at two geographic levels. The upper level is census tracts or tract pairs under the 2010 census geography. The lower level is a regular hexagonal grid implemented with Uber's H3 hierarchical geospatial indexing system. H3 supports 16 resolutions, where each finer resolution has cells with one-seventh of the area of the coarser resolution. I aggregate the parcel-level data described below to resolution-9 hexagons, which in my sample have an average side length of 215 meters (705 feet) and an area of 0.12 square kilometers (29 acres). The radius of the smallest circle that contains a regular hexagon of side 215 meters (circumcircle radius) is 215 meters as well. The radius of the largest circle contained within the hexagon (incircle radius) is 186 meters (611 feet).

Commuting flow data. The source for tract-to-tract commuting flow data is the LEHD Origin Destination Employment Statistics (LODES) data set. I use information on all types of jobs of workers whose workplace and residence are in California. I average the count of workers in each tract-tract pair across the three-year period 2017–2019 to reduce the influence of individual idiosyncrasies on estimation and counterfactuals (Dingel and Tintelnot, 2021).

Place-of-work data. Because LODES reports only a few income bins, I use the 2017 National Household Travel Survey (NHTS) to measure workplace income. With the geocoded detailed version of the data set I match respondents' household incomes to workplace locations and then aggregate them to tracts using the provided weights to make the numbers representative of the total number of workers. Income is reported in 11 bins, and I take the midpoint of each bin except for the top one. When income is missing in a tract, I input the average in the ZIP code. If there are no other tracts in the same ZIP code with non-missing data, I input the average of the five nearest neighbors.

Residential housing data. To construct measures of the number of workers and the average rent in each hexagon, I combine 2019 parcel-level data with data from the U.S. Census American Community Survey (ACS) at block-group level. The parcel data is from the San Diego Association of Governments (SANDAG), the main planning and transportation agency in the region. These data sets have the number of housing units, square footage, and assessed value for each parcel on each plot of land in the County of San Diego. Because California assessment values are not updated every year to market conditions, I combine these records with 18 years of transaction data from ZTRAX to recover parcel-level market-value assessments; Appendix Section B.1 describes the procedure. I then overlay the plots on the hexagonal grid and count the number of housing units to compute the median market value per square foot in each hexagon. To make the housing counts consistent with the tract-level number of workers, I allocate the workers of each tract to hexagons according to the share of housing units. Finally, to obtain the yearly rents per square foot in each hexagon, I rescale the market value per square foot with the ratio of yearly rent to home values in the ACS.

Wildfire risk. I measure wildfire risk using the Burn Probability (BP) data set from the United States Forest Service (Scott et al., 2020). I overlay the hexagonal grid with the original raster data sets at 270-meter spatial resolution and calculate the mean values within each cell. The burn probability represents the annual likelihood of burning in a given location, and I use it as a direct measure of the burn probability in the model, δ_i. This is the worker-side risk object. In the insurance block below, I instead use destructive wildfire risk $\rho_i \equiv \delta_i \times \text{FLEP4}_i$.

The United States Forest Service risk measures are the result of a model developed by Finney et al. (2011) that simulates the occurrence and spread of large wildfires under many hypothetical fire seasons. It is important to use probabilistic measures derived from a model and not the distribution of historical burns because these are rare events. Although it may seem that wildfires are not that rare, because burned area and property damages are on an increasing trend at the state level, at fine resolution the realization of a fire burning is still a low-probability event.

Topography and current weather. I measure current weather as the "normal" in the most recent three decades (1991–2020) with data from the PRISM Climate Group (PRISM, 2020), which I also use to calculate the mean elevation in each hexagon. I measure the distance of each hexagon's centroid to the closest wildland, as well as the fuel types in each hexagon, using the 2019 National Land Cover Database. Lastly, I calculate the mean terrain slope (in percentages) from the United States Geological Survey's Digital Elevation Model raster files.

IV.B Estimation of Location Preferences and Amenity Costs of Wildfire Risk

The amenity costs of wildfires are difficult to measure directly because they bundle a range of effects on health, safety, and comfort. I therefore infer them from the location-choice model. This subsection estimates three sets of worker-side parameters: residential demand with respect to rents, wildfire disamenities, and commuting parameters.

IV.B.1 Residential demand and rent sensitivity

First, I estimate a hexagon-level regression of 2010-2017 changes in log population $\Delta \ln N_i$ on changes in log rents $\Delta \ln Q_i$. The model's location choice equation (2) together with the specification of amenities (5) imply the following equation:

$$\Delta \ln N_i = -\varepsilon(1-\beta)\Delta \ln Q_i - \Delta \ln \gamma_i^{\varepsilon} + \xi_{I(i)} + \Delta \ln b_i^{\varepsilon},$$

where $\xi_{I(i)}$ is a tract-level fixed effect absorbing commuting market access and endogenous amenity feedbacks, and γ_i captures remaining hexagonal determinants of commuting market access. To identify the parameter composite $\varepsilon(1-\beta)$ I need to properly control for changes in hexagonal commuting access costs, $\Delta \ln \gamma_i$. I do so by controlling for distances to freeways and to ramps and the interaction of the two. I am also assuming that over the 2010-2017 period, there were no significant changes in wildfire risk $\Delta\delta_i$ correlated with rents. I believe this assumption to be relatively weak, since the recent stream of high-profile wildfire disasters in California started just after 2017.

Conditional on those controls, I also need variation in local rents $\Delta \ln Q_i$ that is orthogonal to unobserved amenity changes, $\Delta \ln b_i$. To that end, I instrument local rents with a leave-one-out measure of initial surrounding buildup in the same tract in 2010. This captures the local supply tightness faced by hexagon i while excluding its own buildup mechanically. The identifying assumption is that, after conditioning on tract-level demand shifters and observables, initial surrounding buildup may shift the slope of local housing supply, but it cannot directly proxy for within-tract demand shocks such as changes in local amenities, commuting access, or wildfire risk, that affect the reference hexagon.

Table 1 presents the results, with the first stage in column 1 and the second stage estimates in column 2. I obtain an estimate of $\varepsilon(1-\beta) = 3.590$, which combined with a value for $\beta = 0.743$ obtained from matching ACS housing expenditure shares yields an estimated $\varepsilon = 14$. The bootstrapped 95% confidence intervals are $[0.733, 0.752]$ for β and $[8.58, 21.3]$ for ε.

Table 1: Estimates of hex-level preferences

	(1) $\Delta \ln Q_i$	(2) $\Delta \ln N_i$	(3) $\ln \left(N_i^{1/\varepsilon} Q_i^{1-\beta}\right)$
Initial built share	-0.793***		
	(0.142)		
$\Delta \ln Q_i$		-3.590***	
		(0.807)	
$\delta_{i,0\text{ km}}$			-1.264***
			(0.334)
$\delta_{i,0.4\text{ km}}$			-1.774***
			(0.422)
Topo., Weather, Dist. controls			x
Comm. access controls	x	x	
Tract FE	x	x	x
Estimator	OLS	IV	OLS
F-statistic	31.241		
N	17,799	17,799	6,713

Notes: Standard errors clustered by tract in parentheses. Comm. access controls include log distances to freeway and ramp (and their interaction). Topo., Weather, Dist. controls include wildfire/sea distance, slope, and land-cover shares. The full set of estimated coefficients is available in Tables A.2 and A.3. Asterisks indicate 10% (*), 5% (**), and 1% (***) significance.

IV.B.2 Wildfire disamenities

With the estimated β and ε in hand, I estimate the wildfire disamenity parameters φ^B and then translate them into willingness to pay for safety. To quantify the welfare cost of wildfire risk and forecast how the residential amenity values of places at risk will evolve with climate change, I need to separate the effects of wildfire risk from other determinants of the amenity value of an area. This separation is important because wildfire-prone areas are bundled with positive amenities, such as natural beauty, that may dominate the negative risk effect.

I again leverage the model's location choice equation (2) together with the specification of amenities (5) to construct the following estimating equation:

$$\ln(N_i^{1/\varepsilon} Q_i^{1-\beta}) = -\sum_{\ell} \varphi_\ell^B \, \bar{\delta}_{i\ell} + X_i^B \gamma^B + \xi_{I(i)} + e_i.$$

Relative to the amenities in the theory (5), in this specification I included observable controls and I replaced wildfire risk in a hexagon δ_i with a more flexible specification that allows for spatial lags. Formally, I assume that the variable capturing other amenities that are not wildfire safety is $b_i = \exp(\bar{\xi}_I + X_i^B \gamma^B + e_i)$: a function of observable variables X_i^B with parameters γ^B, a component that is fixed within a tract (or coarser-resolution hexagon) $\bar{\xi}_I$, and an unobserved component e_i. The variable $\bar{\delta}_{i\ell}$ is the mean burn probability at ring distance ℓ from hexagon i, and trivially $\bar{\delta}_{i0} = \delta_i$.

I estimate this equation with 2017 data. The controls included in X_i^B are distance to wildland, topographical variables, weather variables, and their squares. Therefore, this specification exploits variation between small hexagons within a tract that are at similar distance from wildland. I also restrict the amenity regression to tracts near the wildland-urban interface, which I define as tracts with at least one resolution-9 hexagon within 5 km of wildland. This focuses identification on comparisons among neighborhoods with more similar unobserved landscape and development characteristics, while still preserving within-tract variation in burn probability because these tracts contain both riskier and safer hexagons.

The fixed effects and controls help address threats to identification of the coefficients φ_ℓ^B. Controlling for topography and weather is important because these characteristics determine burn probabilities and have amenity value. Moreover, topography affects construction costs and therefore housing prices.

Another concern is reverse causation from density to wildfire risk through land-use, firefighting, or human-caused ignitions. The tract fixed effects help address this concern because these mechanisms arguably operate at a larger scale. Having more traffic or recreational use of wildland would increase the likelihood of ignitions; however, that likelihood would be a function of the overall level of development in the area and not of variation between hexagons within a tract.

Additionally, recent wildfire realizations or incomplete information could also bias the estimates. A recent catastrophe could reduce population density only temporarily while homes are rebuilt, thus biasing the amenity damages. I address this concern by excluding from the estimation sample those locations that burned within the previous five years; this is the amount of time it has taken to rebuild destroyed buildings in the past in the United States (Alexandre et al., 2014). Incomplete information, if residents' perceptions of risk are different from objective risk, could also bias the results. This is less of a concern with wildfire risk because wildfires' recurrence in this area makes the risk salient. Moreover, myopia would bias the amenity costs towards zero, so my estimates would be conservative.

An important implicit assumption is that current prices reflect only the current risk, but do not anticipate the future changes in risk. Violations of this assumption could bias the estimated preferences and, as a consequence, call into question the use of the model for counterfactual analyses of other environmental risks or projections of wildfire risk (Severen et al., 2018). I believe that anchoring my estimation in 2017, before the recent stream of catastrophic California wildfires, helps assuage these concerns.

The estimated amenity costs of wildfires are large but localized. Column 3 of Table 1 presents the results of estimating this equation by OLS. Relative to columns 1 and 2, column 3 uses fewer observations because the amenity regression is estimated only on near-interface tracts and excludes hexagons that burned within the previous five years. This specification includes only one spatial lag, defined as the neighboring hexagons (with centroid-to-centroid distance of approximately 400 meters). I select the number of lags after running a flexible lag specification with 5 lags, shown in Figure A.3, which shows that the remaining tail effect beyond one lag is economically small and statistically negligible. I estimate disamenity parameters of $\varphi^B_{0km} = 1.264$ and $\varphi^B_{0.4km} = 1.774$, with 95% bootstrapped confidence intervals of $[0.575, 2.66]$ and $[0.693, 3.28]$, respectively.

The interpretation of these parameters is the marginal willingness to pay for a reduction in burn probability as a fraction of income. The riskiest bin of Figure 2 has average burn probabilities between 0.04 and 0.06, so $\varphi^B_{0km} = 1.264$ implies residents would be willing to pay between 5.1% and 7.6% of annual income to avoid the wildfire risk they face. I also calculate the willingness to pay for safety considering burn probabilities in both the home hexagon and neighboring hexagons and obtain that, across populated hexagons, the average willingness to pay to remove risk is 3.5% of income, and the 95th percentile is 12.6%. To put these numbers in perspective, the average combined employee health insurance premium contribution and deductible in the United States in 2019 was 11.5% of median income, and 11.7% in California (Collins et al., 2022). This is, of course, an incomplete measure of the welfare effects of the wildfire disamenities because it ignores the general equilibrium effects that would arise from changing allocations and prices. I calculate more comprehensive equivalent variations to risk reductions in Section V.

Table A.3 in the appendix reports two IV specifications that address the main endogeneity concerns. In both cases, the estimates remain statistically significant and larger than the baseline comparable estimate in column 4, suggesting that the baseline results may be conservative. Column 5 addresses reverse causation from human development to burn probability by instrumenting burn probability with the non-anthropogenic wildfire risk measure of Parisien et al. (2012), which removes the direct effect of human presence on wildfire risk. Column 6 addresses the concern that climate and topography may directly affect amenities by using variation in expected risk driven by the salience of nearby burns, measured as the cumulative burn history before 2010 of other hexagons in the same tract.

IV.B.3 Commuting parameters

The final estimation step on the worker side of the model estimates the parameters controlling the commuting disutility (γ^D) and the dispersion in effective wages (θ). I estimate these parameters in two steps, which I explain in more detail in the appendix (Section E). I first estimate a commuting gravity equation with workplace and residential tract fixed effects using 2017 commuting flows that yields the composite $\theta\gamma^D$ (Table A.4). I then identify θ from a regression of the workplace tract fixed effect on log wages. I instrument workplace wages in 2017 with a destination-specific leave-one-out market-access predictor of 2010 wages (Table A.5). The estimated values are $\gamma^D = 0.0285$ and $\theta = 3.13$. The 95% bootstrap confidence intervals are $[0.0256, 0.0314]$ and $[2.86, 3.47]$, respectively. This estimate of θ is similar in magnitude to the local extensive-margin labor supply elasticity estimated by Severen (2019) for Los Angeles, whose preferred estimate is 2.18.

IV.C Estimation of Markup Elasticities of Housing Supply

This subsection estimates how local markup elasticities, and thus the steepness of local housing supply, vary across space. I estimate Equation 11 at the hexagon-8 level using 2010–2017 changes, allowing the markup elasticity to depend on baseline buildup and terrain slope and instrumenting housing growth with lagged nearby job-access growth. The estimates imply higher markup elasticities in more built-out and steeper locations, and the implied hexagon-level markup elasticities decline with wildfire risk.

Table 2 reports the estimates of Equation 11, clustering standard errors by hexagon-7. To match the implemented specification, I let the markup elasticity vary with initial log buildup and terrain slope:

$$\mu_i = \mu_H + \mu_U\,(\ln u_{i,2010} - \overline{\ln u}_{2010}) + \mu_S\,(slope_i - \overline{slope}).$$

The coefficient μ_H is therefore the markup elasticity at mean initial log buildup and mean slope. The interaction term μ_U captures whether inverse supply is steeper in places that were already more built out, while μ_S captures whether inverse supply is also steeper in physically constrained locations. I include slope because effective development capacity is determined not only by regulatory limits: even holding fixed formal capacity, steeper terrain may constrain the structures that can be built.

The endogenous terms are $\Delta \ln H_i$ and its interactions with initial log buildup and slope. I instrument these variables with a predetermined job-access shifter based on 2001–2010 growth in nearby parcel-based job counts, weighted by $\exp(-d/2)$ and aggregated to hexagon-8, together with the corresponding interaction instruments. Identification therefore requires that, conditional on baseline buildup and slope, this lagged demand shifter affects 2010–2017 rent growth only through induced housing-demand pressure and the resulting movement along the supply curve, rather than through direct changes in local development costs.

Table 2: Estimates of the housing supply curve

	(1) $\Delta \ln Q_i$	(2) $\Delta \ln Q_i$
$\Delta \ln H_i$	-0.029***	0.935***
	(0.010)	(0.354)
$\Delta \ln H_i \times$ Initial log buildup	0.007	0.587**
	(0.010)	(0.259)
$\Delta \ln H_i \times$ Slope	0.003	0.240*
	(0.005)	(0.141)
Initial log buildup	0.006**	-0.068**
	(0.003)	(0.032)
Slope	-0.012***	-0.024*
	(0.002)	(0.014)
Constant	0.508***	0.360***
	(0.004)	(0.050)
Estimator	OLS	IV
N	2,659	2,659
1st-stage Wald ($\Delta \ln H_i$)		62.849 [$\chi^2(3)$]
1st-stage Wald ($\Delta \ln H_i \times$ Initial log buildup)		37.484 [$\chi^2(3)$]
1st-stage Wald ($\Delta \ln H_i \times$ Slope)		79.070 [$\chi^2(3)$]

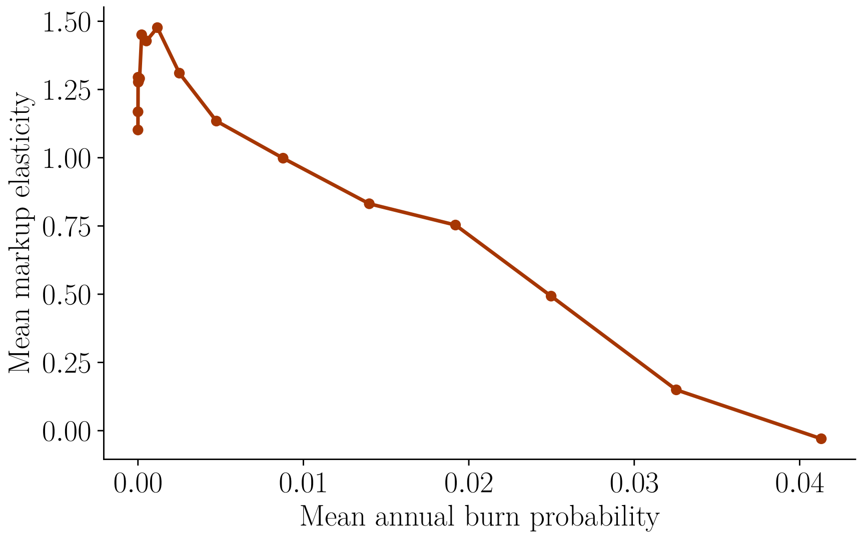
Notes: OLS and IV regressions of housing-price growth on housing-quantity growth and its interactions with baseline buildup and slope. Standard errors in parentheses clustered by resolution-7 hexagon. First-stage entries report Wald statistics for the excluded instruments. Asterisks indicate 10% (*), 5% (**), and 1% (***) significance.

The OLS estimates are not economically plausible: the coefficient on $\Delta \ln H_i$ is negative, and both interaction terms are small and statistically insignificant. This pattern is consistent with substantial endogeneity or measurement-error bias. By contrast, the IV estimates are more in line with the model. The baseline markup elasticity is positive, $\mu_H = 0.935$ (95% bootstrap confidence interval: $[0.504, 3.07]$), and the interaction with initial log buildup is also positive, $\mu_U = 0.587$ (95% bootstrap confidence interval: $[0.243, 1.7]$), implying steeper inverse supply in places that were already closer to capacity in 2010. The slope interaction is likewise positive, $\mu_S = 0.240$ (95% bootstrap confidence interval: $[0.0899, 1.16]$).

The implied markup elasticities μ_i decline with wildfire risk. Combining the estimated parameters μ_H, μ_U, and μ_S with buildup and slope measurements, I compute μ_i for each hexagon. Table A.6 shows summary statistics for their distribution. The population-weighted average markup elasticity is 1.19, with 10th and 90th percentiles of 0.671 and 1.766, respectively. Using population weights, 98.8% of the estimated μ_i are positive. Figure 4 shows a binned scatter plot of markup elasticities against wildfire risk. Average markup elasticities range from 1.2 to 1.5 in the safest areas and decline to below 0.2 in the riskiest areas.

In the simulations in the next section, I let μ_i vary with 2017 buildup, so locations that are

Figure 4: The Wildfire Risk Gradient of Estimated Markup Elasticities



Notes: Binned scatter plot of the 2010 estimated markup elasticities against average wildfire risk, weighting by population within bins.

more built out in 2017 can have different local supply elasticities. However, I center $\ln u_{i,2017}$ using the 2010 mean, not the 2017 mean. This preserves the normalization in the estimation, where μ_H is identified at average 2010 buildup, and avoids shifting the entire elasticity schedule simply because average buildup changed over time. The average markup elasticity in 2017 rises to 1.243, and the 10th and 90th percentiles increase to 0.775 and 1.792, respectively.

IV.D Estimation of Premium Schedules and Property Damages

The model links wildfire risk to housing development costs and, in turn, to landowners' construction and pricing decisions. Wildfire risk raises development costs through expected property damages and through the cost of insuring those losses. Moreover, if regulation constrains premiums in the wildfire risk pool below expected losses, insurers recoup the shortfall by increasing premiums for other (non-wildfire) perils. In this section, I use ZIP-by-year panel data on insurance premiums and fire coverage in California to estimate the model parameters governing pricing frictions in wildfire premiums (τ), wildfire damages (φ^H), and non-wildfire insurance costs ($p^o\varphi^o$).

I first use variation in average premiums and fire coverage to estimate the destructive wildfire risk premium schedule $p_i = p(\rho_i; \tau) = \tau\rho_i$. The model implies that average premiums $\bar{p}^*_{z,t}$ (including both wildfire and non-wildfire perils) for ZIP code z and year t are given by

$$\bar{p}^*_{z,t} = \tau\, \bar{\rho}_{z,t}\bar{x}_{z,t} + \beta_x\bar{x}_{z,t} + \bar{\tau}_z + \bar{\tau}_t + \tilde{\tau}_{z,t}, \tag{14}$$

where $\bar{\rho}_{z,t}$ is the housing-unit-weighted average destructive wildfire probability within ZIP code z, $\bar{x}_{z,t}$ is average fire coverage, $\bar{\tau}_z$ and $\bar{\tau}_t$ are ZIP-code and year fixed effects, and $\tilde{\tau}_{z,t}$ is the regression residual. I include $\bar{x}_{z,t}$ separately to absorb changes in non-wildfire premiums that scale with coverage.

As shown in the Appendix, the residual in Equation 14 contains two terms that may bias estimation of τ: a term capturing time-varying non-wildfire premiums and insurance demand, and a term capturing the within-ZIP covariance between destructive wildfire risk and coverage. To better account for non-wildfire premiums beyond ZIP-code and year fixed effects, I include controls that shape insurance demand independently of destructive wildfire risk but may still be spuriously correlated with risk: the share of homes with a mortgage, the share vacant, the share used seasonally, and median year built. In Appendix Table A.7, I also address the covariance term by interacting the baseline within-ZIP covariance between units and destructive wildfire probability with year dummies; the results remain robust.

Second, I use variation in total premiums and in the distribution of housing units across exposed and unexposed locations to estimate the composite parameters $\tau\varphi^H$ and $p^o\varphi^o$. Together with τ, these identify wildfire damages φ^H. Replacing the model-implied expressions for coverage demand (6), total premiums in ZIP code z and year t satisfy

$$p^*_{z,t} \quad = \quad (\tau\varphi^H) \sum_{i\in z} \rho_i H_{i,t} + (p^o\varphi^o)\, H_{z,t} + \bar{\varphi}_z + \bar{\varphi}_t + \tilde{\varphi}_{z,t}. \tag{15}$$

This equation implies increasing housing in locations with no wildfire risk within a ZIP code ($\rho_i = 0$) increases total premiums by $p^o\varphi^o$. If housing instead expands in risky locations, total premiums increase by an additional $\tau\varphi^H$ times the increase in ZIP-level exposure $\sum_{i\in z} \rho_i H_{i,t}$. When estimating this equation, I include the same insurance-demand controls as Equation 14.

To estimate Equations 14 and 15, I combine ZIP-code-level insurance data with unit-weighted exposure measures constructed from Census block data for 2010 and 2018. The CDI data provide average premiums ($\bar{p}^*_{z,t}$) and average fire coverage ($\bar{x}_{z,t}$) at the ZIP-code level every other year. To calculate housing-unit-weighted average destructive wildfire probabilities $\bar{\rho}_{z,t}$, I begin at the Census-block level and then aggregate to ZIP codes using a Census concordance. For each block, I define destructive wildfire risk as $\rho_i \equiv \delta_i \times \text{FLEP4}_i$: the product of the probability that a wildfire burns a pixel and the conditional probability that flame length exceeds 4 feet. Both objects come from the USFS. I construct total exposure ($\sum_{i\in z} \rho_i H_{i,t}$) similarly, by multiplying block-level destructive wildfire risk by the number of housing units and then aggregating to ZIP codes. Due to data limitations, I use units instead of housing space to construct $\sum_{i\in z} \rho_i H_{i,t}$ and $H_{z,t}$.[8]

My estimates imply that destructive wildfire risk is significantly underpriced in California. Table 3 reports the results of estimating Equation 14 (Column 1) and Equation 15 (Column 2). I estimate $\tau = 0.895$, implying premium rates 10.5% below actuarially fair pricing ($p_i = \rho_i$). Using the more realistic benchmark of fair pricing plus an 18% risk load ($p_i = R\rho_i$ with $R = 1.18$), premium rates underprice this benchmark premium by 24.1%. The estimates in Column 2 show a composite parameter $\tau\varphi^H = \$64,498.8$, which, combined with the estimate of τ, implies wildfire damages

[8] Accordingly, I interpret the estimated damage parameters as per-unit equivalents of the model's per-space objects; this normalization is mostly innocuous for counterfactuals that depend on ratios and cost shares, and matters only if average housing space per unit varies systematically with wildfire risk within ZIP codes.

of $\varphi^H = \$72,040.9$.[9] The coefficient on total units implies that the cost of non-wildfire risks is $p^o \varphi^o = \$293.6$.

Table 3: Estimates of wildfire risk premiums and property damages

	Average Premium	Total Premium
	(1)	(2)
Avg. Destruction prob. × Avg. Coverage	0.895***	
	(0.145)	
Avg. Coverage	0.00139***	
	(0.000397)	
Total Exposure		64,498.8***
		(23,285.4)
Total Units		293.6***
		(49.00)
Insurance controls	Yes	Yes
Year FE	Yes	Yes
ZIP-code FE	Yes	Yes
N	2,610	2,578

Notes: OLS regressions at ZIP-code level. Standard errors in parentheses clustered by ZIP code. Asterisks indicate 10% (*), 5% (**), and 1% (***) significance. Appendix Tables A.7 and A.8 present the full set of estimated coefficients.

Through the lens of the model, these parameters matter quantitatively through the equilibrium changes in housing development costs and insurance premiums (Equations 12 and 13, respectively). For the former, I back out the baseline wildfire ($\varphi^H \tau \rho_i / D_i$) and other-risk ($\varphi^o p^o / D_i$) development cost shares by proxying the unobserved baseline unit development cost d_i with an annualized reconstruction cost to construct the denominator D_i. The implicit assumption is that the estimated reconstruction cost is similar in magnitude to the upfront cost of developing a home. My estimates imply that wildfire insurance costs account for 8.2% of housing development costs on average across inhabited hexagons. The 90th, 95th, and maximum are 27.3%, 30.8%, and 43.5%. Other non-wildfire perils account for 6.4% on average.

To implement the equilibrium funding condition in Equation 13, I also need to measure the premium shares ϖ^o and ϖ_i, which are a function of the estimated premium schedule and property damages. Approximating total premiums by their damage component (and ignoring the distortion term), the wildfire premium share can be approximated with the housing wildfire exposure share: $\varpi_i \approx \rho_i H_i / (\sum_{i'} \rho_{i'} H_{i'})$. These are only a function of data. The share of total wildfire to non-wildfire

[9] The implied wildfire damages are lower than the reconstruction costs in Boomhower et al. (2024), which average about $\$594,671$. Their sample is selected from homes in ZIP codes with high average risk, which could explain the larger magnitude. Under this interpretation, my estimates are a lower bound on expected property damages.

premiums becomes

$$\varpi^o \approx \frac{\tau\varphi^H}{p^o\varphi^o}\sum_i \frac{H_i}{H}\rho_i.$$

Using the estimates of $\tau\varphi^H$ and $p^o\varphi^o$ from Table 3, and the average housing exposure $\sum_i H_i\rho_i/H$ in the San Diego Metro, I obtain $\varpi^o = 0.227$. Noting that in 13 the value of ϖ^o is the cross elasticity between wildfire and non-wildfire premiums, this magnitude implies that (all else equal) raising wildfire premiums by 10% would reduce the premiums of other perils by 2.27%.

IV.E Estimation of Future and Endogenous Wildfire Risk

To explore the effects of future increases in wildfire risk driven by climate change, I need estimates of future risk. Therefore, I estimate the historical relation between maximum temperatures and burn probabilities, and then use the estimates to predict future wildfire risk under forecast temperatures in the year 2060. In robustness exercises, I also allow wildfire risk to adjust endogenously with housing density, so I extend the estimated equation to include housing unit density as a regressor.

Historical wildfires and weather. To estimate the relation between temperature and wildfire risk, I use data on past wildfire burns and temperatures between 1981 and 2019 in California. I compute the average maximum summer temperature by year and resolution-7 hexagon using monthly data from PRISM (2020). I identify hexagons that burn each year from the maps of wildfire perimeters published by CAL FIRE (FRAP, 2019), considering as burned a resolution-9 hexagon that has more than 80% of its area within a wildfire perimeter.

Future weather. I obtain measures of future and current maximum temperatures from the Localized Climate Analogues (LOCA) Downscaled Climate Projections from Cal-Adapt (Cal-Adapt, 2018; Pierce et al., 2018). There are projections under different emissions scenarios and from different climate models. The RCP 4.5 scenario represents a medium emissions future where societies work to reduce greenhouse gas emissions. The RCP 8.5 scenario represents a "business as usual" future that is used to explore a higher emissions scenario. I use four global climate models that represent a range of possible futures for California (Pierce et al., 2018). First, I download the daily projections for maximum temperatures until the year 2060 and compute the average maximum temperature during the summer of each year. Then I map pixels to resolution-5 hexagons in Southern California using the closest distance between centroids. Last, I average the maximum temperatures over 30-year periods.

Housing density. I construct housing-unit counts from Census block totals for 1990, 2000, and 2010 by merging them to a USDA WUI block-to-hex crosswalk and allocating each block's housing stock across hexagons according to the share of block area that overlaps each hexagon. I then sum these weighted counts to the H3 resolution-7 analysis grid, and create an annual series by linearly interpolating between census years and extrapolating to 1981 and 2019. I compute each hexagon's area geodesically in square kilometers and define housing density as annual housing units divided by hexagon area.

Estimation. I estimate the following regression:

$$Fire_{jt} = \exp\left[\alpha^T \ln T_{jt} + \alpha^P \ln(N_{jt}/L_{jt}) + \xi_j + \xi_t + e_{jt}\right],$$

where j identifies a resolution-7 hexagon, t is a year between 1981 and 2019, $Fire_{jt}$ is a dummy that indicates a wildfire burn, T_{jt} is the average summer maximum temperature in degrees Celsius, N_{jt}/L_{jt} is housing density, measured in housing units per km2; ξ_j and ξ_t denote spatial and year fixed effects, respectively; and e_{jt} is a residual. I mark a resolution-7 hexagon as burning during a given year if at least one of its children that are resolution-9 hexagons burned. I estimate this regression with data for the entire state of California. Table A.9 in the appendix shows the estimates, where columns differ in the sets of included fixed effects. My preferred specification (column 4), which uses year and resolution-5 hexagon fixed effects, yields estimates $\widehat{\alpha}^T = 3.036$ and $\widehat{\alpha}^P = -0.157$. Appendix Figure A.4 shows that a more flexible binned specification yields a monotonic decrease in burn probability with housing density, supporting the claim that the non-monotonicity concern discussed in Section II.A.1 is not important in this setting.

I then use the estimated elasticity of wildfire probability with respect to temperature together with climate projections to generate simple predictions of future wildfire risk driven by climate change. I assign the same resolution-7 temperature to all resolution-9 children and compute counterfactual wildfire risk δ_i' as a function of current risks δ_i, the ratio of future average temperatures $\bar{T}_i'$ to current average temperatures $\bar{T}_i$, and the elasticity estimated above: $\delta_i' = \delta_i\,(\bar{T}_i'/\bar{T}_i)^{\alpha^T}$. In counterfactuals where I allow wildfire risk to be endogenous, I combine the temperature adjustment above with an adjustment based on tract-level housing-unit density changes: $\delta_i' = \delta_i\,(\bar{T}_i'/\bar{T}_i)^{\alpha^T}\,(N_{I(i)}'/N_{I(i)})^{\alpha^P}$. For the insurer-side object, I then set $\rho_i' = \rho_i\,(\delta_i'/\delta_i)$, holding FLEP4_i fixed because I do not separately project changes in fire intensity.

IV.F Calibration of additional parameters

I calibrate two sets of non-estimated preference parameters. Details are left to the appendix.

First, I treat endogenous amenity feedbacks as a robustness extension rather than as part of the baseline specification. In the baseline, I set $(\eta^W, \eta^N) = (0, 0)$ so that local amenities depend only on exogenous fundamentals and wildfire disamenities. For robustness, I allow amenities to rise with tract income and fall with tract density, and I discipline the relative and absolute magnitudes of these effects using external evidence on the mediation of density disamenities by income and on the capitalization of local income into housing values. This procedure implies small elasticities, with benchmark positive-feedback calibrations such as $(0.02, 0.06)$, so a 10% increase in tract income raises amenities by 0.2%, while a 10% increase in tract density lowers amenities by 0.6%.

Second, I calibrate the within-neighborhood elasticity of substitution across housing units, ζ, using the equivalence between my one-level CES housing aggregator and a multinomial logit model in which log rent enters utility with coefficient $1 - \zeta$. I map estimates from Ouazad and Rancière (2019) into this object: their rent-based specification implies a relatively high elasticity (about 4), while their house-price specification implies a much lower elasticity (about 1.1–1.3). Because substitution in my setting likely lies between these renter and owner extremes, I set $\zeta = 2.5$ as a midpoint baseline.

V Counterfactual Scenarios

In this section, I first analyze targeted policy counterfactuals that change housing capacity in Transit Priority Areas (TPAs) and shift insurance pricing to cost-based premiums. These targeted-policy results report the direct welfare effects of changing the policy environment at current wildfire risk. I then turn to the welfare cost of wildfire risk (WCW), which asks a different question: holding a given policy environment fixed, how much welfare would be gained by reducing wildfire probabilities? I use WCW to compare those targeted reforms with *aggregate distortion counterfactuals* that shift the insurance-pricing or housing-capacity distortions uniformly across space. Across these exercises, the main result is that insurance pricing and housing supply interact strongly in determining the incidence of wildfire costs. In the benchmark specification, targeted housing reform attenuates the worker-side burden of cost-based insurance pricing.

Worker welfare is measured as a money-metric change in worker values, while landowner welfare is measured using a profit-based financial-incidence statistic. For landowners, this statistic is based on changes in profit flows, omits the direct certainty-equivalent insurance term, and uses a constant-share approximation to weight baseline profits; Appendix C gives the exact formulas.

After presenting the targeted policy experiments, I study WCW in the current equilibrium, then in future scenarios, and finally under endogenous amenity feedbacks and endogenous wildfire risk.

V.A Targeted policy counterfactuals

I consider two targeted reforms motivated by recent California efforts to encourage homebuilding, including SB 9 and SB 10 (Sisson, 2022). First, I explore the effects of up-zoning areas within half a mile of a major transit stop in the City of San Diego—known as Transit Priority Areas (TPAs). I implement this scenario by increasing housing capacity $\bar{H}_i$ by 15% in those areas. TPAs account for 8.11% of baseline housing capacity. Accordingly, a 15% increase in TPA capacity implies a 1.22% increase in total permitted building space. Below, I benchmark this targeted housing reform against a uniform citywide 10% increase in capacity.

Second, I evaluate a cost-based insurance pricing schedule that eliminates cross-subsidization. I implement this reform by setting premiums in the new equilibrium to $p_i' = 1.18\,\rho_i$. This schedule follows Boomhower et al. (2024) and corresponds to setting premiums equal to expected losses plus an 18 percent risk load. Through the lens of the model, this corresponds to setting the wildfire risk premium parameter equal to the risk load, $\tau' = R$, which effectively implements a market structure in which the wildfire and non-wildfire risk pools are self-funded. This reform reverses the pattern of cross-subsidization evident in Figure 1. Figure 5 summarizes the spatial equilibrium effects of these targeted reforms to housing capacity and insurance premiums.

Up-zoning TPAs reduces rents across the city, especially in safer areas. Panel a of Figure 5 illustrates this result with a binned scatter plot of counterfactual rent changes (y-axis) against burn probabilities (x-axis). On average, rents in the city fall by 2.1%, but in the riskiest bins the drop is only about 0.5%. Aggregate results are reported in Table A.10. This pattern arises because wildfire risk and TPAs are spatially correlated: major transit stops tend to be located in central parts of the city, far from the high-risk urban periphery. Falling rents in central areas lead to a reallocation of residents from high-risk areas toward areas that do not burn, as shown in Panel b. While the safest bins grow up to 2%, the riskiest ones shrink by about 2.6%.

This reallocation benefits workers but creates both winners and losers among landowners. Workers are better off as rents fall, with the largest improvements in residential values in the safest areas (Panel c). In present-value terms, workers' welfare increases by $7.5 billion. Welfare impacts are reported in Table 4. Landowner gains are concentrated in relatively safe areas, but profits fall in most locations (Panel d). In total, landowners suffer a present-value-equivalent loss of $5.3 billion, which brings the utilitarian net effect of the policy reform to $2.2 billion. Because baseline landowner profits are weighted using a constant-share approximation, gains attributed to safer, more built-out locations should be interpreted conservatively.

Table 4: Welfare effects of reform counterfactuals (million dollars, present value)

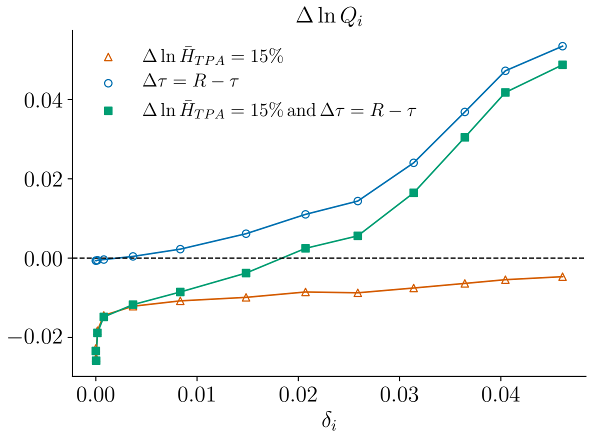
	(1) Workers	(2) Safe LO	(3) Risky LO	(4) All LO	(5) Total
Panel A. Aggregate distortion counterfactuals: welfare effect					
Uniform insurance change ($\Delta\tau = 10\%$)	7	458	-245	213	220
Uniform building change ($\Delta \ln \bar{H}_i = 10\%$)	15,892	-8,324	-2,670	-10,994	4,897
Joint uniform change	15,909	-7,874	-2,919	-10,793	5,116
Panel B. Policy counterfactuals: welfare effects					
Cost-based insurance ($\Delta\tau = R - \tau$)	-5	1,328	-799	529	525
TPA up-zoning ($\Delta \ln \bar{H}_{TPA} = 15\%$)	7,480	-3,769	-1,542	-5,311	2,170
Joint targeted reform	7,494	-2,456	-2,346	-4,802	2,692

Notes: This table uses the baseline no-amenity specification ($\eta_W = 0$, $\eta_N = 0$, $\alpha_P = 0$). Values are millions of dollars in present value and report welfare changes relative to the baseline equilibrium. Positive values denote welfare gains; negative values denote welfare losses. Aggregate distortion counterfactuals apply uniform changes to insurance pricing or housing capacity across space. Policy counterfactuals use cost-based insurance pricing and targeted up-zoning within Transit Priority Areas (TPAs).

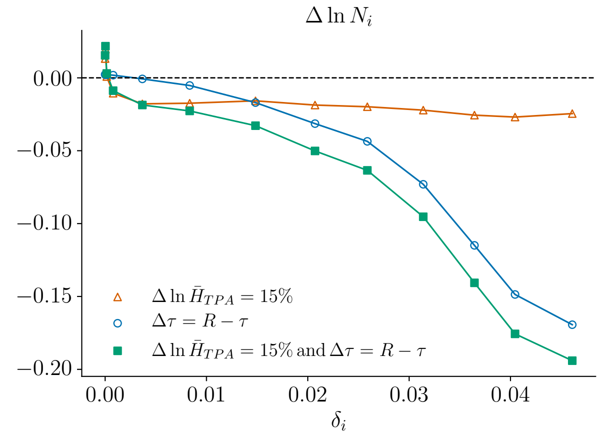
Relative to a uniform citywide 10% increase in capacity, the TPA reform delivers roughly 45% of the rent, housing, and welfare effects while expanding total permitted space by only 1.22% rather than 10%. The uniform benchmark lowers average log rents by 4.9% and raises housing by 6.6%, compared with 2.1% and 2.9% under TPA up-zoning. Worker welfare rises by 0.83% ($809.82 per household-year, or $15.9 billion in present value), while landowner profits fall by 5.5% ($560.26 per home-year, or $11.0 billion in present value), for a net gain of $4.9 billion. This comparison

Figure 5: Targeted policy counterfactuals

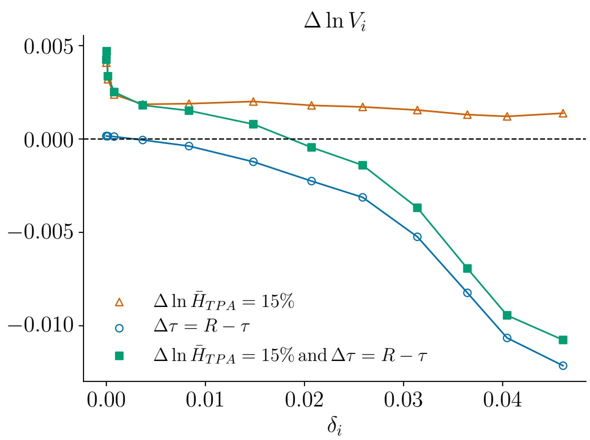
(a) Effects on rents



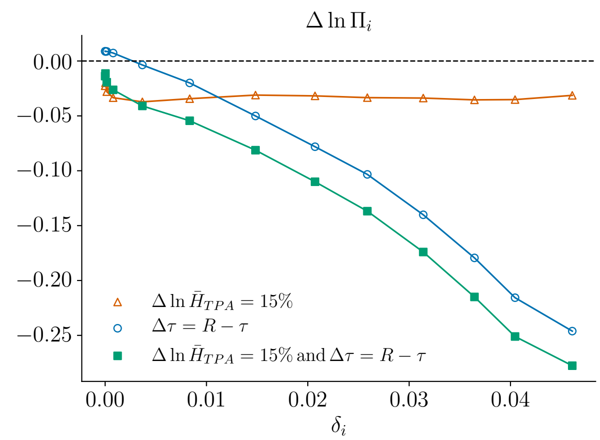
(b) Effects on populations



(c) Effects on workers' welfare



(d) Effects on landowners' welfare



Note: Binned scatter plots of simulated counterfactual changes (y-axis) vs. annual burn probabilities (x-axis).

suggests that the aggregate effects of housing-supply reform are disproportionately concentrated in relatively safe, supply-constrained central neighborhoods.

The insurance market reform eliminating cross-subsidization reduces housing development costs in relatively safer areas and increases them in the riskiest areas. Housing costs for landowners fall by about 0.5% in the safest areas and rise by up to 10.6% in the riskiest areas (Appendix Figure A.5). As a result, rents increase in most locations, with larger increases in areas with higher burn probabilities (Panel a of Figure 5). Rents fall slightly in the safest locations, but increase by about 5.3% in the riskiest ones. Population therefore decreases in the riskiest areas and increases in relatively safer ones (Panel b). The rise in rents dominates the welfare effects for workers, who are worse off overall, though the aggregate effect is small. Landowners in areas where insurance premiums fall benefit (Panel d), while those facing higher premiums experience losses. In present value, owners of safe land gain an equivalent of $1.3 billion, while owners of risky land lose $800 million.

Each panel in Figure 5 also plots the effect of implementing the two reforms jointly, which alters the risk gradient of the equilibrium effects of these reforms. Pairing the insurance market reform with the TPA-targeted relaxation of building constraints steepens the gradient of rent changes against wildfire risk, as the safest locations become even cheaper. This magnifies the reallocation out of the riskiest places (Panel b), with the riskiest areas losing up to 19.4% of their residents. In terms of welfare, the TPA-targeted reform shifts the incidence of the insurance market reform away from workers, as the gradient of worker values shifts upward (Panel c) while the gradient of landowner profits shifts downward (Panel d). These results suggest that the two distortions interact in determining the incidence of the cost of wildfire risks, a point I return to in the next section.

Direct welfare effects versus WCW

To keep the objects distinct, let $W(\delta, \mathcal{S})$ denote total welfare when wildfire risk is δ and the policy environment is $\mathcal{S}$, where $\mathcal{S}$ summarizes insurance pricing and housing capacity. The targeted policy results above report the direct welfare effect of moving from the current policy regime to a reform regime at current wildfire risk: $W(\delta, \mathcal{S}') - W(\delta, \mathcal{S})$. By contrast, WCW under a given regime $\mathcal{S}$ is the money-metric gain from lowering wildfire risk to a low-risk benchmark while holding that regime fixed: $W(\delta^{low}, \mathcal{S}) - W(\delta, \mathcal{S})$, reported as a positive cost. These two objects need not move in the same direction. For example, cost-based insurance raises total welfare in Table 4, but it also raises WCW in Table 5. Removing cross-subsidies can improve the policy allocation at current wildfire risk even as it makes the remaining wildfire risk more costly for the groups that are exposed to it. For landowners, the appendix distinguishes between full certainty-equivalent welfare and the financial-incidence measure that I quantify, which is based on changes in profit flows and omits the direct utility effect of changes in insurance distortions and risk-bearing. The appendix states the exact welfare formulas used below.

V.B The current welfare cost of wildfire risk

The targeted policy experiments above describe how reforms reshape the spatial equilibrium and the direct welfare effects of changing the policy environment. I now turn to the welfare cost of wildfire risk itself. WCW is the money-metric welfare gain from reducing wildfire probabilities while holding the rest of the policy environment fixed. This risk reduction sets each location's burn probability to the 1st-percentile threshold whenever its observed probability exceeds that value, and leaves lower-risk locations unchanged. This object is useful for separating the direct amenity and damage costs of wildfire risk from the way housing-supply and insurance distortions redistribute those costs in equilibrium.

I consider two kinds of WCW counterfactuals. First, I study *aggregate distortion counterfactuals*, where I shift the insurance-pricing distortion or the housing-capacity distortion uniformly across space. These exercises are not intended to mimic a specific policy reform. Instead, they quantify how the aggregate welfare burden of wildfire risk responds to city-wide changes in each distortion. Because locations differ in wildfire risk, amenities, and supply elasticities, the incidence of these uniform distortion changes is spatially heterogeneous in equilibrium. Second, I study *policy counterfactuals*, where the insurance reform is set to cost-based pricing and the housing reform targets TPAs. These targeted reforms are interesting both because they are realistic and because TPAs overlap relatively safe and supply-constrained parts of San Diego.

Table 5 reports the baseline WCW levels and counterfactual changes in present value under the no-amenity specification. I use this benchmark because it shuts down endogenous amenity feedbacks, relies on fewer externally calibrated parameters, and stays closer to the estimated core model.

Table 5: Welfare cost of wildfire risk and counterfactual changes

	(1) Workers	(2) Safe LO	(3) Risky LO	(4) All LO	(5) Total
Panel A. Baseline WCW level					
Baseline	15,466	-6,259	8,254	1,995	17,461
Panel B. Aggregate distortion counterfactuals: change in WCW					
Uniform insurance change ($\Delta \ln \tau = 10\%$)	118	-287	297	10	127
Uniform building change ($\Delta \ln \bar{H}_i = 10\%$)	-757	672	260	932	175
Joint uniform change	-650	394	561	955	305
Interaction (joint - separate)	-11	9	4	13	2
Panel C. Policy counterfactuals: change in WCW					
Cost-based insurance ($\Delta\tau = R - \tau$)	359	-843	944	101	460
TPA up-zoning ($\Delta \ln \bar{H}_{TPA} = 15\%$)	-475	357	115	472	-3
Joint targeted reform	-136	-470	1,065	595	458
Interaction (joint - separate)	-20	16	5	21	1

Notes: This table uses the baseline no-amenity specification ($\eta_W = 0$, $\eta_N = 0$, $\alpha_P = 0$). Values are millions of dollars in present value. Panel A reports the welfare cost of wildfire risk (WCW). Panels B and C report changes in WCW relative to the Panel A level. Positive values denote higher WCW; negative values denote lower WCW. A negative Panel A value means that wildfire risk benefits that group in equilibrium. Aggregate distortion counterfactuals apply uniform changes to insurance pricing or housing capacity across space. Policy counterfactuals use cost-based insurance pricing and targeted up-zoning within Transit Priority Areas (TPAs).

Wildfire risk imposes a present-value cost of \$17.5 billion in the aggregate, with significant heterogeneity in its incidence (Panel A). Workers bear \$15.5 billion of this cost and owners of risky land bear \$8.3 billion, while owners of safe land receive a \$6.3 billion offsetting gain through equilibrium scarcity effects. The average yearly cost on workers amounts to \$788.1 per household, or 0.80% of income. For owners of land at risk of wildfire, the yearly cost is \$2,226.7 per home and 17.6% of profits. Landowners in safe areas receive a benefit worth \$393.2 per home (4.1% of profits), although this offsetting gain is likely conservative because the constant-share approximation understates baseline profit shares in safer, more built-out locations.

The aggregate distortion counterfactuals (Panel B) show that the two distortions play different roles: insurance frictions shift the incidence to owners of safe land, and building constraints shift it to workers. A uniform increase in the sensitivity of insurance premiums to wildfire risk raises aggregate WCW by $127 million, increasing the burden on workers and owners of risky land while increasing the gains to owners of safe land. A uniform relaxation of building constraints has a much larger incidence effect: worker WCW falls by $757 million, but the offsetting gains to owners of safe land shrink by $672 million and the cost borne by owners of risky land rises by $260 million, so aggregate WCW increases by $175 million. Under the joint uniform change, aggregate WCW rises by $305 million, while the interaction term remains close to zero ($2 million).

The policy counterfactuals (Panel C) preserve the same qualitative insurance result, but in the benchmark no-amenity specification the targeted building reform mainly affects incidence rather than aggregate WCW. Moving to cost-based insurance pricing raises aggregate WCW by $460 million. Up-zoning TPAs changes aggregate WCW by only -$3 million, but lowers worker costs by $475 million while raising total landowner costs by $472 million. When combined, the two reforms raise aggregate WCW by $458 million. The joint reform still lowers worker WCW by $136 million, but it increases the burden borne by owners of risky land by $1.07 billion. I interpret this benchmark result as showing that targeted up-zoning can reallocate the burden created by cost-based insurance; below I show that the aggregate effect, and whether the joint reform lowers worker WCW relative to baseline, are sensitive to amenity feedbacks and endogenous wildfire risk.

The aggregate interaction remains small because the joint reform has offsetting incidence effects across groups, even though those incidence effects are economically meaningful. The last two rows of Panels B and C show the change in WCW induced by jointly changing both distortions and the difference between that experiment and the sum of changing them separately. In the policy case (Panel C), the aggregate interaction is again only $1 million relative to a $458 million joint effect. For workers, however, the interaction accounts for 14.9% of the effect of the joint reform. For landowners, it reduces the benefits to owners of safe land by 3.4% and has a negligible effect on owners of risky land. This stronger incidence effect is driven by the targeting of the building-capacity reform: in the uniform counterfactuals (Panel B), the interaction accounts for only 1.7% of the reduction in worker costs.

V.C Future wildfire costs

Future wildfire costs are higher because climate change raises aggregate WCW, while population growth shifts more of the incidence to workers (Tables 6, A.11, and A.12). Relative to the current no-amenity baseline, aggregate WCW rises from $17.5 billion to $20.5 billion in the combined future. A climate-change-only future already raises aggregate WCW to $20.6 billion, while a population-growth-only future leaves it essentially unchanged at $17.4 billion. Nearly all of the future increase in aggregate WCW therefore comes from higher wildfire risk rather than from a larger city. Population growth still matters for incidence, however, because worker WCW rises from $15.5 billion to $16.1 billion while total landowner WCW falls from $2.0 billion to $1.3 billion,

Table 6: Future welfare cost of wildfire risk and counterfactual changes

	(1) Workers	(2) Safe LO	(3) Risky LO	(4) All LO	(5) Total
Panel A. Baseline WCW level					
Baseline	17,877	-7,955	10,542	2,587	20,464
Panel B. Aggregate distortion counterfactuals: change in WCW					
Uniform insurance change ($\Delta \ln \tau = 10\%$)	106	-288	384	96	202
Uniform building change ($\Delta \ln \bar{H}_i = 10\%$)	-874	774	301	1,075	201
Joint uniform change	-777	494	688	1,182	405
Interaction (joint - separate)	-9	8	3	11	2
Panel C. Policy counterfactuals: change in WCW					
Cost-based insurance ($\Delta \tau = R - \tau$)	323	-844	1,213	368	691
TPA up-zoning ($\Delta \ln \bar{H}_{TPA} = 15\%$)	-558	420	135	556	-2
Joint targeted reform	-254	-409	1,353	944	690
Interaction (joint - separate)	-19	15	5	20	1

Notes: This table uses the future baseline with climate change and population growth and the baseline no-amenity specification ($\eta_W = 0$, $\eta_N = 0$, $\alpha_P = 0$). Values are millions of dollars in present value. Panel A reports the welfare cost of wildfire risk (WCW). Panels B and C report changes in WCW relative to the Panel A level. Positive values denote higher WCW; negative values denote lower WCW. A negative Panel A value means that wildfire risk benefits that group in equilibrium. Aggregate distortion counterfactuals apply uniform changes to insurance pricing or housing capacity across space. Policy counterfactuals use cost-based insurance pricing and targeted up-zoning within Transit Priority Areas (TPAs).

consistent with tighter housing supply shifting wildfire costs toward workers.

Climate change also drives most of the change in the future policy counterfactuals, while leaving the aggregate effect of TPA up-zoning close to zero. Under climate change alone, the aggregate effect of cost-based insurance rises from \$460 million to \$699 million and the joint targeted reform from \$458 million to \$697 million, almost identical to the \$691 million and \$690 million effects in the combined future. By contrast, the population-growth-only economy leaves those aggregate policy effects close to their current values, at \$451 million and \$451 million. TPA up-zoning remains nearly neutral in the aggregate in all future scenarios, with effects between -\$3 million and -\$2 million, even though the worker-side benefit becomes somewhat larger in magnitude. I therefore interpret the future exercises as showing that climate change raises the aggregate stakes of insurance distortions, whereas population growth mainly sharpens their distributional consequences through housing supply.

V.D Robustness

Allowing endogenous amenity feedbacks does not materially affect the estimated welfare costs of wildfire risk, but can dampen the building-side effects (Table A.13). The aggregate baseline

WCW and the insurance counterfactuals remain close to the no-amenity benchmark: aggregate WCW falls only slightly from $17.5 billion to $17.2 billion, the uniform insurance change from $127 million to $114 million, and cost-based insurance from $460 million to $415 million. The larger differences arise for housing reforms. With endogenous amenity feedbacks, the aggregate effect of uniform building relaxation falls from $175 million to $57 million, TPA up-zoning moves from essentially zero to a $44 million reduction in WCW, and the worker effect of the joint targeted reform flips from -$136 million to +$30 million. These changes indicate that the targeted up-zoning result is not a robust aggregate policy prescription. I therefore use the no-amenity specification as the baseline for exposition, but interpret the positive-amenity calibration as showing that amenity feedbacks can materially reshape incidence.

Endogenizing wildfire risk leaves the main conclusions intact (Table A.15). Relative to the no-amenity baseline, aggregate WCW rises only slightly, from $17.5 to $17.6 billion, and the uniform building-expansion counterfactual is essentially unchanged, from $175 to $169 million. By contrast, insurance reforms become more costly: the aggregate effect of a uniform insurance change rises from $127 to $148 million, and the effect of cost-based pricing rises from $460 to $530 million. The main qualitative change is that TPA up-zoning no longer lowers aggregate WCW, with its effect moving from about zero to a $29 million increase. The future endogenous-wildfire exercise yields the same pattern, so I interpret this extension as strengthening the insurance results while weakening any claim that targeted up-zoning reduces aggregate WCW.

VI Conclusion

This paper shows that urban institutions play a central role in shaping exposure to wildfire risk. In San Diego, stringent land-use regulations in safer central neighborhoods, combined with insurance pricing that weakly reflects underlying risk, help push development toward the fire-prone urban fringe. Using a quantitative spatial equilibrium model disciplined by detailed data on zoning, wildfire risk, insurance, and commuting, I quantify the amenity costs of wildfire exposure and the way these costs interact with housing supply.

Aggregate distortion counterfactuals reveal that the two distortions affect wildfire costs differently. Economy-wide increases in insurance pricing raise the cost of wildfire risk borne by workers and owners of risky land, while relaxing building constraints mainly redistributes wildfire costs from workers toward landowners by eroding scarcity gains on safe land. Targeted up-zoning of central, low-risk areas can likewise reallocate burden, attenuating the worker-side burden created by cost-based insurance in the benchmark specification, but its aggregate effect on WCW is modest and model-dependent. The interaction between the two reforms is therefore most robustly interpreted as an incidence result rather than as evidence that this particular up-zoning reform neutralizes aggregate wildfire costs. Taken together, these results highlight a key policy trade-off: zoning and insurance reforms jointly shape who bears wildfire costs, while the aggregate effect of targeted supply reform depends on how amenities and wildfire risk respond in equilibrium.

References

Acosta, C. (2021): "The Incidence of Land Use Regulations," *SSRN Electronic Journal*.

Alexandre, P., M. Mockrin, S. Stewart, R. Hammer, and V. Radeloff (2014): "Rebuilding and new housing development after wildfire," *International Journal of Wildland Fire*, 24.

Anagol, S., F. V. Ferreira, and J. Rexer (2021): "Estimating the Economic Value of Zoning Reform," *SSRN Electronic Journal*.

Andela, N., D. C. Morton, L. Giglio, Y. Chen, G. R. van der Werf, P. S. Kasibhatla, R. S. DeFries, G. J. Collatz, S. Hantson, S. Kloster, D. Bachelet, M. Forrest, G. Lasslop, F. Li, S. Mangeon, J. R. Melton, C. Yue, and J. T. Randerson (2017): "A human-driven decline in global burned area," *Science*, 356, 1356–1362, doi: 10.1126/science.aal4108.

Balboni, C. (2021): "In Harm's Way? Infrastructure Investments and the Persistence of Coastal Cities," Working paper, Department of Economics, Massachusetts Institute of Technology.

Baum-Snow, N. and L. Han (2024): "The Microgeography of Housing Supply," *Journal of Political Economy*, 132, 1897–1946.

Baylis, P. and J. Boomhower (2019): "Moral Hazard, Wildfires, and the Economic Incidence of Natural Disasters," Working paper.

Baylis, P. W. and J. Boomhower (2021): "Mandated vs. Voluntary Adaptation to Natural Disasters: The Case of U.S. Wildfires," *National Bureau of Economic Research Working Paper Series*, No. 29621.

Boehm, C. E. and N. Pandalai-Nayar (2022): "Convex Supply Curves," *The American Economic Review*, 112, 3941–3969.

Boomhower, J., M. Fowlie, J. Gellman, and A. Plantinga (2024): "How Are Insurance Markets Adapting to Climate Change? Risk Classification and Pricing in the Market for Homeowners Insurance," Working Paper 32625, National Bureau of Economic Research.

Burke, M., M. L. Childs, B. D. la Cuesta, M. Qiu, J. Li, C. F. Gould, S. Heft-Neal, and M. Wara (2023): "Wildfire Influence on Recent US Pollution Trends," *National Bureau of Economic Research Working Paper Series*, No. 30882, author contact info: Marshall Burke Doerr School of Sustainability Stanford University Stanford, CA 94305 E-Mail: mburke@stanford.edu Marissa Childs Center for the Environment Harvard University E-Mail: mchilds@fas.harvard.edu Brandon De la Cuesta Stanford University SIEPR, Gunn Building Stanford, CA 94305 E-Mail: brandon.delacuesta@stanford.edu Minghao Qiu E-Mail: mhqiu@stanford.edu Jessica Li 473 Via Ortega Stanford, CA 94305 USA E-Mail: jbli@stanford.edu Carlos F. Gould Department of

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Burke, M., A. Driscoll, J. Xue, S. Heft-Neal, J. Burney, and M. Wara (2020): "The Changing Risk and Burden of Wildfire in the US," Working Paper 27423, National Bureau of Economic Research.

Cal-Adapt (2018): "LOCA Derived Data," Data derived from LOCA Downscaled CMIP5 Climate Projections. Cal-Adapt website developed by University of California at Berkeley's Geospatial Innovation Facility under contract with the California Energy Commission. Retrieved August 8, 2022 from https://cal-adapt.org/.

CAL FIRE (2025): "Top 20 Destructive and Deadliest California Wildfires," California Department of Forestry and Fire Protection statistics sheets. Accessed March 28, 2026.

Cignarale, T., J. Laucher, K. Allen, and L. Landsman-Smith (2017): "The Availability and Affordability of Coverage for Wildfire Loss in Residential Property Insurance in the Wildland-Urban Interface and Other High-Risk Areas of California: CDI Summary and Proposed Solutions," .

Collins, S. R., D. C. Radley, and J. C. Baumgartner (2022): "Trends in Employer Health Care Coverage, 2010–2020," *Commonwealth Fund*.

Correia, S., P. Guimarães, and T. Zylkin (2020): "Fast Poisson estimation with high-dimensional fixed effects," *The Stata Journal*, 20, 95–115.

Costinot, A., D. Donaldson, and C. Smith (2016): "Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World," *Journal of Political Economy*, 124, 205–248.

Cruz, J.-L. (2021): "Global Warming and Labor Market Reallocation," Working paper.

Cruz, J.-L. and E. Rossi-Hansberg (2021): "The Economic Geography of Global Warming," Working Paper 28466, National Bureau of Economic Research.

Desmet, K., R. E. Kopp, S. A. Kulp, D. K. Nagy, M. Oppenheimer, E. Rossi-Hansberg, and B. H. Strauss (2021): "Evaluating the Economic Cost of Coastal Flooding," *American Economic Journal: Macroeconomics*, 13, 444–86.

Dingel, J. I. and F. Tintelnot (2021): "Spatial Economics for Granular Settings," Tech. rep.

Favilukis, J., P. Mabille, and S. V. Nieuwerburgh (2022): "Affordable Housing and City Welfare," *The Review of Economic Studies*, rdac024.

Finney, M. A., C. W. McHugh, I. C. Grenfell, K. L. Riley, and K. C. Short (2011): "A simulation of probabilistic wildfire risk components for the continental United States," *Stochastic Environmental Research and Risk Assessment*, 25, 973–1000.

FRAP (2019): "The California Department of Forestry and Fire Protection's Fire and Resource Assessment Program (FRAP)," Data retrieved May 28, 2020 from https://frap.fire.ca.gov/.

Garnache, C. (2020): "Does the Salience of Risk Affect Large, Risky Asset Prices?" *SSRN Electronic Journal*.

Gellman, J., M. Walls, and M. J. Wibbenmeyer (2021): "Wildfire, Smoke, and Outdoor Recreation in the Western United States," Working Paper 21-22, Resources for the Future (RFF).

Gyourko, J. and S. E. McCulloch (2024): "The Distaste for Housing Density," Working Paper 33078, National Bureau of Economic Research.

Gyourko, J. and R. Molloy (2015): "Chapter 19 - Regulation and Housing Supply," in *Handbook of Regional and Urban Economics*, ed. by G. Duranton, J. V. Henderson, and W. C. Strange, Elsevier, vol. 5 of *Handbook of Regional and Urban Economics*, 1289 – 1337.

Hsiao, A. (2025): "Sea Level Rise and Urban Adaptation in Jakarta," Working paper, April 27, 2025 draft.

Issler, P., R. H. Stanton, C. Vergara-Alert, and N. E. Wallace (2020): "Mortgage Markets with Climate-Change Risk: Evidence from Wildfires in California," *SSRN Electronic Journal*.

Jia, R., X. Ma, and V. W. Xie (2022): "Expecting Floods: Firm Entry, Employment, and Aggregate Implications," NBER Working Papers 30250, National Bureau of Economic Research, Inc.

Kim, M.-K. and P. M. Jakus (2019): "Wildfire, national park visitation, and changes in regional economic activity," *Journal of Outdoor Recreation and Tourism*, 26, 34–42.

Knorr, W., A. Arneth, and L. Jiang (2016a): "Demographic controls of future global fire risk," *Nature Climate Change*, 6, 781–785.

Knorr, W., L. Jiang, and A. Arneth (2016b): "Climate, CO_2 and human population impacts on global wildfire emissions," *Biogeosciences*, 13, 267–282.

Knorr, W., T. Kaminski, A. Arneth, and U. Weber (2014): "Impact of human population density on fire frequency at the global scale," *Biogeosciences*, 11, 1085–1102.

LTDB (2010): "Longitudinal Tract Data Base (LTDB)," Data retrieved August 1, 2020 from http://www.s4.brown.edu/us2010/Researcher/Bridging.htm.

Macek, J. (2024): "Housing Regulation and Neighborhood Sorting across the United States," Job Market Paper, University of Toronto. Version dated November 2, 2024.

Martynov, P. (2021): "Welfare Effects of Zoning: Density Restrictions and Heterogeneous Spillovers," Job market paper, University of California, Berkeley.

McConnell, K., S. Whitaker, E. Fussell, J. DeWaard, K. Price, and K. Curtis (2021): "Effects of Wildfire Destruction on Migration, Consumer Credit, and Financial Distress," *FRB of Cleveland Working Paper*.

Molnar, P. (2022): "Over the next few years, will San Diego County's population continue to decline?" *The San Diego Union-Tribune*.

Nath, I. (2021): "The Food Problem and the Aggregate Productivity Consequences of Climate Change," *SSRN Electronic Journal*.

Oh, S. S., I. Sen, and A.-M. Tenekedjieva (2026): "Pricing of Climate Risk Insurance: Regulation and Cross-Subsidies," *The Journal of Finance*.

Ospital, A. (2025): "Housing Supply and Natural Hazards within and across US Cities," *AEA Papers and Proceedings*, 115, 380–84.

Ostriker, A. and A. Russo (2026): "The Effects of Floodplain Regulation on Housing Markets," Working paper, March 2, 2026 draft.

Ouazad, A. and R. Rancière (2019): "CITY EQUILIBRIUM WITH BORROWING CONSTRAINTS: STRUCTURAL ESTIMATION AND GENERAL EQUILIBRIUM EFFECTS," *International Economic Review*, 60.

Parisien, M.-A., S. Snetsinger, J. A. Greenberg, C. R. Nelson, T. Schoennagel, S. Z. Dobrowski, and M. A. Moritz (2012): "Spatial variability in wildfire probability across the western United States," *International Journal of Wildland Fire*, 21, 313–327.

Pierce, D. W., J. F. Kalansky, and D. R. Cayan (2018): "Climate, Drought, and Sea Level Rise Scenarios for the Fourth California Climate Assessment," .

PRISM (2020): "PRISM Climate Group, Oregon State University," Data retrieved August 3, 2022 from https://prism.oregonstate.edu.

Richardson, L. A., P. A. Champ, and J. B. Loomis (2012): "The hidden cost of wildfires: Economic valuation of health effects of wildfire smoke exposure in Southern California," *Journal of Forest Economics*, 18, 14–35.

Rollet, V. (2025): "Zoning and the Dynamics of Urban Redevelopment," Working paper.

Saiz, A. (2010): "The Geographic Determinants of Housing Supply*," *The Quarterly Journal of Economics*, 125, 1253–1296.

SANDAG (2019): "Housing in the San Diego Region: Building permits, cost, and vacancies," .

Scott, J. H., J. W. Gilbertson-Day, C. Moran, G. K. Dillon, K. C. Short, and K. C. Vogler (2020): "Wildfire Risk to Communities: Spatial datasets of landscape-wide wildfire risk components for the United States," Tech. rep., Forest Service Research Data Archive, Fort Collins, CO.

Severen, C. (2019): "Commuting, labor, and housing market effects of mass transportation: Welfare and identification," .

Severen, C., C. Costello, and O. Deschênes (2018): "A Forward-Looking Ricardian Approach: Do land markets capitalize climate change forecasts?" *Journal of Environmental Economics and Management*, 89, 235–254.

Sisson, P. (2022): "San Diego Tackles California's Housing Crisis and Car-Centric Design," *Planning Magazine*.

Watson, C. L. and O. Ziv (2025): "A Test for Pricing Power in Urban Housing Markets," *The Review of Economics and Statistics*, 1–33.

Xu, R., P. Yu, M. J. Abramson, F. H. Johnston, J. M. Samet, M. L. Bell, A. Haines, K. L. Ebi, S. Li, and Y. Guo (2020): "Wildfires, Global Climate Change, and Human Health," *N Engl J Med*, 383, 2173–2181.

Housing Supply, Property Insurance, and Exposure to Wildfire Risk

Appendices for Online Publication

Augusto Ospital

Appendix Contents

A Additional Figures And Tables

A.1 Estimation tables

Table A.1: Bootstrap parameter estimates

Parameter	Estimate	99% CI	95% CI
β	0.743	[0.732, 0.754]	[0.733, 0.752]
ε	14.0	[7.28, 26.2]	[8.58, 21.3]
φ^B_{0km}	1.26	[0.41, 3.21]	[0.575, 2.66]
$\varphi^B_{0.4km}$	1.77	[0.334, 3.85]	[0.693, 3.28]
γ_D	0.0285	[0.0251, 0.0325]	[0.0256, 0.0314]
θ	3.13	[2.75, 3.55]	[2.86, 3.47]
μ_H	0.935	[0.427, 8.29]	[0.504, 3.07]
μ_U	0.587	[0.158, 3.58]	[0.243, 1.7]
μ_S	0.24	[0.0644, 3.4]	[0.0899, 1.16]

Notes: Bootstrap draws tracts with replacement and re-runs the full estimation procedure. This captures joint estimation uncertainty, which is missed by inspecting separate regression outputs. Iterations: 1,000. Confidence intervals are percentile intervals from the bootstrap distribution.

Table A.2: Estimates of the hex-level relationships

	(1) $\Delta \ln Q_i$	(2) $\Delta \ln N_i$	(3) $\Delta \ln Q_i$	(4) $\Delta \ln N_i$
Initial built share	-0.785***		-0.793***	
	(0.141)		(0.142)	
$\Delta \ln Q_i$		-3.703***		-3.590***
		(0.832)		(0.807)
ln(km to freeway)			0.000	-0.015
			(0.004)	(0.020)
ln(km to ramp)			-0.011*	-0.048*
			(0.006)	(0.026)
ln(km to freeway) × ln(km to ramp)			-0.002	-0.008
			(0.002)	(0.007)
Tract FE	x	x	x	x
Estimator	OLS	IV	OLS	IV
F-statistic	30.833		31.241	
N	17,799	17,799	17,799	17,799
R^2	0.279	-	0.281	-
R^2 Within	0.002	-	0.005	-

Notes: Standard errors clustered by tract in parentheses. Asterisks indicate 10% (*), 5% (**), and 1% (***) significance.

Table A.3: Estimates of the amenity effects

	$\ln\left(N_i^{1/\varepsilon} Q_i^{1-\beta}\right)$				
	(1)	(3)	(4)	(5)	(6)
$\delta_{i,0\text{ km}}$	-1.264***	-1.246***	-2.036***	-4.853***	-5.671**
	(0.334)	(0.334)	(0.348)	(1.521)	(2.838)
$\delta_{i,0.4\text{ km}}$	-1.774***	-1.561***			
	(0.422)	(0.450)			
ln(km to wildland)	0.013***	0.012***	0.014***	0.013***	0.008
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)
ln(km to sea)	-0.029**	-0.029**	-0.030**	-0.037***	-0.037***
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)
Slope	-0.001	-0.002	-0.002	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Forest share	-0.089*	-0.091*	-0.095*	-0.082*	-0.081*
	(0.050)	(0.050)	(0.051)	(0.046)	(0.048)
Shrub share	-0.191***	-0.192***	-0.196***	-0.177***	-0.168***
	(0.009)	(0.009)	(0.009)	(0.015)	(0.021)
Grass share	-0.167***	-0.170***	-0.172***	-0.145***	-0.134***
	(0.013)	(0.013)	(0.013)	(0.021)	(0.034)
ln(km to freeway)		0.003	0.003	0.002	0.004
		(0.004)	(0.004)	(0.004)	(0.004)
ln(km to ramp)		-0.005	-0.006	-0.006	-0.005
		(0.004)	(0.004)	(0.004)	(0.004)
ln(km to freeway) × ln(km to ramp)		-0.004***	-0.004***	-0.004***	-0.004***
		(0.001)	(0.001)	(0.001)	(0.001)
Parisien BP				73.803*	
				(39.049)	
Max temp.				0.055**	0.034
				(0.025)	(0.037)
Elevation				0.000***	0.000***
				(0.000)	(0.000)
Max VPD				-0.029**	-0.017
				(0.013)	(0.019)
Tract FE	x	x	x	x	x
Estimator	OLS	OLS	OLS	IV	IV
Instrument				Parisien-topo	Hist. burn
F-statistic				20.539	7.325
N	6,713	6,713	6,713	6,713	6,713

Notes: Standard errors clustered by tract in parentheses. Asterisks indicate 10% (*), 5% (**), and 1% (***) significance. Instrument labels are abbreviated as Parisien-topo for the interaction of non-anthropogenic Parisien burn probability with topography and weather, and Hist. burn for leave-out pre-2010 cumulative burn history.

Table A.4: Estimates of the commuting relationships

	(1) $\ln N_{IJ,10}$	(2) $\ln N_{IJ,17}$
Distance_{IJ}	-0.083***	-0.089***
	(0.002)	(0.001)
Work-tract FE	x	x
Tract FE	x	x
Estimator	OLS	OLS
N	107,479	107,479
R^2	0.716	0.737
R^2 Within	0.486	0.537

Notes: Standard errors two-way clustered by tract-pair in parentheses. Distance is measured in miles. Asterisks indicate 10% (*), 5% (**), and 1% (***) significance.

Table A.5: Estimates of the wage and work relationships

	(1) $\ln W_{J,17}$	(2) Work $\text{FE}_{J,17}$
$\ln \hat{W}_{J,10}$	16.814***	
	(3.386)	
$\ln W_{J,17}$		3.134***
		(0.651)
Constant	-180.897***	-34.905***
	(38.722)	(7.394)
Estimator	OLS	IV
F-statistic	26.376	
N	613	613
R^2	0.041	-
Adj. R^2	0.040	-

Notes: Robust standard errors in parentheses. Asterisks indicate 10% (*), 5% (**), and 1% (***) significance.

Table A.6: Distribution of estimated μ_i

	2010		2017	
	Unweighted	Weighted	Unweighted	Weighted
Mean	0.935	1.190	0.983	1.243
S.D.	0.721	0.466	0.715	0.445
Min	-1.699	-1.699	-1.500	-1.500
P10	-0.112	0.671	-0.057	0.775
P25	0.570	0.891	0.636	0.973
Median	1.015	1.175	1.071	1.208
P75	1.402	1.461	1.433	1.475
P90	1.749	1.766	1.781	1.792
Max	4.594	4.594	4.689	4.689
Share positive	88.1%	98.8%	88.9%	99.1%

Notes: Summary statistics for the estimated μ_i distribution across hexagons. Weighted columns use hex-level housing-unit counts as weights, with 2010 columns weighted by $N_{i,2010}$ and 2017 columns weighted by $N_{i,2017}$. Share positive reports the fraction of hexagons with $\mu_i > 0$.

Table A.7: Estimates of wildfire risk premiums in property insurance

	Average premium					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Destruction prob.	0.927***	0.895***	0.831***	0.958***	0.927***	0.862***
× Avg. Coverage	(0.144)	(0.145)	(0.187)	(0.153)	(0.155)	(0.198)
Avg. Coverage	0.00136***	0.00139***	0.00156***	0.00136***	0.00139***	0.00156***
	(0.000364)	(0.000397)	(0.000480)	(0.000365)	(0.000398)	(0.000481)
Mortgage share		36.48	20.57		38.76	20.97
		(88.93)	(87.06)		(88.43)	(86.52)
Seasonal share		6.462	-550.0**		25.04	-528.8**
		(222.6)	(223.8)		(222.6)	(225.7)
Vacant share		228.6	534.7***		226.4	529.2***
		(183.5)	(192.8)		(183.6)	(193.4)
Year built		-0.700	-3.211*		-0.614	-3.114*
		(1.495)	(1.684)		(1.501)	(1.688)
Rented share			-4250.4*			-4194.4*
			(2430.1)			(2432.0)
Home value			-0.201			-0.200
			(0.164)			(0.164)
Covariance				-1242.4*	-1247.3*	-1012.6
× Yr=2010				(738.8)	(714.6)	(738.9)
Covariance				-605.8	-613.3	-578.4
× Yr=2018				(732.1)	(706.8)	(720.7)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
ZIP code FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,666	2,610	2,576	2,666	2,610	2,576
R^2	0.974	0.973	0.975	0.974	0.973	0.976

Notes: OLS regressions at ZIP-code level. Standard errors in parentheses clustered by ZIP code. Asterisks indicate 10% (*), 5% (**), and 1% (***) significance.

Table A.8: Estimates of property damages implicit in insurance premiums

	Total premium		
	(1)	(2)	(3)
Exposure	44490.3**	41505.7*	64498.8***
	(22551.7)	(22607.0)	(23285.4)
Units	296.2***	312.1***	293.6***
	(47.27)	(48.44)	(49.00)
Mortgage share		-1586293.6***	-1803521.2***
		(462902.6)	(482409.8)
Seasonal share		627807.5	1621428.9**
		(612639.9)	(628620.8)
Vacant share		-675003.5	-1626028.0***
		(534956.5)	(556507.0)
Year built		-16663.0***	-20412.9***
		(4584.8)	(5606.9)
Rented share			-2152132.0
			(3279947.4)
Home value			1.319***
			(0.265)
Year FE	Yes	Yes	Yes
ZIP code FE	Yes	Yes	Yes
N	2,676	2,614	2,578
R^2	0.986	0.986	0.987

Notes: OLS regressions at ZIP-code level. Standard errors in parentheses clustered by ZIP code. Asterisks indicate 10% (*), 5% (**), and 1% (***) significance.

Table A.9: The historical link between wildfire risk, maximum temperatures, and population density

	(1) Fire	(2) Fire	(3) Fire	(4) Fire
ln(Summer Max. Temp.)	8.675***	8.556***	4.231***	3.036***
	(2.139)	(2.980)	(0.855)	(0.726)
ln(Homes per km2)	-0.059	-0.077	-0.158***	-0.157***
	(0.076)	(0.066)	(0.012)	(0.012)
Constant	-32.488***	-31.984***	-18.031***	-13.850***
	(7.356)	(10.223)	(2.952)	(2.487)
Year FE	No	Yes	No	Yes
Hex FE	Yes	Yes	No	No
Res-5 hex FE	No	No	Yes	Yes
Observations	195,853	195,853	670,609	670,609
Log pseudolikelihood	-36,997	-36,229	-45,166	-44,318

Notes: Poisson pseudo-maximum likelihood regressions (Correia et al., 2020). The units of observation are Uber H3 hexagons at resolution 7. The variable *Fire* is a dummy that indicates the hexagon burned that year. The summer maximum temperatures are the June–August average temperature in degrees Celsius. The wildfire occurrences are constructed from CAL FIRE data (FRAP, 2019). The temperature data is from PRISM (2020). The standard errors are one-way clustered at the level of resolution-5 hexagons by year and shown in parentheses. Asterisks indicate 10% (*), 5% (**), and 1% (***) significance.

A.2 Counterfactuals

Table A.10: Aggregate endogenous responses to reform counterfactuals (weighted means)

	(1) $\Delta \ln Q_i$	(2) $\Delta \ln H_i$	(3) $\Delta \ln N_i$
Panel A. Aggregate distortion counterfactuals: welfare effect			
Uniform insurance change ($\Delta\tau = 10\%$)	0.00002	-0.00002	-0.00001
Uniform building change ($\Delta \ln \bar{H}_i = 10\%$)	-0.04883	0.06649	0.02198
Joint uniform change	-0.04883	0.06646	0.02195
Panel B. Policy counterfactuals: welfare effects			
Cost-based insurance ($\Delta\tau = R - \tau$)	0.00018	-0.00030	-0.00015
TPA up-zoning ($\Delta \ln \bar{H}_{TPA} = 15\%$)	-0.02129	0.02902	0.00939
Joint targeted reform	-0.02114	0.02870	0.00919

Notes: This table uses the baseline no-amenity specification ($\eta_W = 0$, $\eta_N = 0$, $\alpha_P = 0$). Values are baseline-household-weighted means of hex-level endogenous responses, using baseline equilibrium households N_i as weights. The table reports $\Delta \ln Q_i$, $\Delta \ln H_i$, $\Delta \ln N_i$. Positive values denote increases in the corresponding endogenous outcome. Aggregate distortion counterfactuals apply uniform changes to insurance pricing or housing capacity across space. Policy counterfactuals use cost-based insurance pricing and targeted up-zoning within Transit Priority Areas (TPAs).

Table A.11: Climate-change-only future welfare cost of wildfire risk and counterfactual changes

	(1) Workers	(2) Safe LO	(3) Risky LO	(4) All LO	(5) Total
Panel A. Baseline WCW level					
Baseline	17,238	-7,421	10,753	3,332	20,570
Panel B. Aggregate distortion counterfactuals: change in WCW					
Uniform insurance change ($\Delta \ln \tau = 10\%$)	100	-282	387	105	204
Uniform building change ($\Delta \ln \bar{H}_i = 10\%$)	-820	727	284	1,011	191
Joint uniform change	-729	452	674	1,126	398
Interaction (joint - separate)	-9	7	3	11	2
Panel C. Policy counterfactuals: change in WCW					
Cost-based insurance ($\Delta\tau = R - \tau$)	305	-826	1,221	394	699
TPA up-zoning ($\Delta \ln \bar{H}_{TPA} = 15\%$)	-532	400	129	529	-3
Joint targeted reform	-246	-412	1,355	943	697
Interaction (joint - separate)	-18	14	5	19	1

Notes: This table uses the future climate-change-only baseline and the baseline no-amenity specification ($\eta_W = 0$, $\eta_N = 0$, $\alpha_P = 0$). Values are millions of dollars in present value. Panel A reports the welfare cost of wildfire risk (WCW). Panels B and C report changes in WCW relative to the Panel A level. Positive values denote higher WCW; negative values denote lower WCW. A negative Panel A value means that wildfire risk benefits that group in equilibrium. Aggregate distortion counterfactuals apply uniform changes to insurance pricing or housing capacity across space. Policy counterfactuals use cost-based insurance pricing and targeted up-zoning within Transit Priority Areas (TPAs).

Table A.12: Population-growth-only future welfare cost of wildfire risk and counterfactual changes

	(1) Workers	(2) Safe LO	(3) Risky LO	(4) All LO	(5) Total
Panel A. Baseline WCW level					
Baseline	16,058	-6,752	8,061	1,310	17,367
Panel B. Aggregate distortion counterfactuals: change in WCW					
Uniform insurance change ($\Delta \ln \tau = 10\%$)	125	-295	293	-1	124
Uniform building change ($\Delta \ln \bar{H}_i = 10\%$)	-807	716	275	991	184
Joint uniform change	-693	431	573	1,004	311
Interaction (joint - separate)	-11	10	4	14	3
Panel C. Policy counterfactuals: change in WCW					
Cost-based insurance ($\Delta \tau = R - \tau$)	382	-865	934	69	451
TPA up-zoning ($\Delta \ln \bar{H}_{TPA} = 15\%$)	-499	376	121	497	-2
Joint targeted reform	-138	-473	1,061	589	451
Interaction (joint - separate)	-21	17	6	22	1

Notes: This table uses the future population-growth-only baseline and the baseline no-amenity specification ($\eta_W = 0$, $\eta_N = 0$, $\alpha_P = 0$). Values are millions of dollars in present value. Panel A reports the welfare cost of wildfire risk (WCW). Panels B and C report changes in WCW relative to the Panel A level. Positive values denote higher WCW; negative values denote lower WCW. A negative Panel A value means that wildfire risk benefits that group in equilibrium. Aggregate distortion counterfactuals apply uniform changes to insurance pricing or housing capacity across space. Policy counterfactuals use cost-based insurance pricing and targeted up-zoning within Transit Priority Areas (TPAs).

Table A.13: Welfare cost of wildfire risk and counterfactual changes (Amenity externalities)

	(1) Workers	(2) Safe LO	(3) Risky LO	(4) All LO	(5) Total
Panel A. Baseline WCW level					
Baseline	11,631	-2,293	7,844	5,551	17,182
Panel B. Aggregate distortion counterfactuals: change in WCW					
Uniform insurance change ($\Delta \ln \tau = 10\%$)	93	-245	266	21	114
Uniform building change ($\Delta \ln \bar{H}_i = 10\%$)	-368	285	140	425	57
Joint uniform change	-282	45	409	454	172
Interaction (joint - separate)	-7	5	3	8	1
Panel C. Policy counterfactuals: change in WCW					
Cost-based insurance ($\Delta\tau = R - \tau$)	290	-723	847	124	415
TPA up-zoning ($\Delta \ln \bar{H}_{TPA} = 15\%$)	-247	151	52	203	-44
Joint targeted reform	30	-563	902	339	369
Interaction (joint - separate)	-13	8	3	11	-1

Notes: This table uses the specification with amenity externalities ($\eta_W = 0.02$, $\eta_N = 0.06$, $\alpha_P = 0$). Values are millions of dollars in present value. Panel A reports the welfare cost of wildfire risk (WCW). Panels B and C report changes in WCW relative to the Panel A level. Positive values denote higher WCW; negative values denote lower WCW. A negative Panel A value means that wildfire risk benefits that group in equilibrium. Aggregate distortion counterfactuals apply uniform changes to insurance pricing or housing capacity across space. Policy counterfactuals use cost-based insurance pricing and targeted up-zoning within Transit Priority Areas (TPAs).

Table A.14: Future welfare cost of wildfire risk and counterfactual changes (Amenity externalities)

	(1) Workers	(2) Safe LO	(3) Risky LO	(4) All LO	(5) Total
Panel A. Baseline WCW level					
Baseline	13,507	-3,385	9,901	6,516	20,023
Panel B. Aggregate distortion counterfactuals: change in WCW					
Uniform insurance change ($\Delta \ln \tau = 10\%$)	90	-255	344	89	179
Uniform building change ($\Delta \ln \bar{H}_i = 10\%$)	-429	330	164	494	65
Joint uniform change	-345	79	511	590	245
Interaction (joint - separate)	-6	4	3	7	1
Panel C. Policy counterfactuals: change in WCW					
Cost-based insurance ($\Delta\tau = R - \tau$)	279	-751	1,089	337	617
TPA up-zoning ($\Delta \ln \bar{H}_{TPA} = 15\%$)	-294	180	62	242	-52
Joint targeted reform	-27	-563	1,154	591	564
Interaction (joint - separate)	-12	8	3	11	-1

Notes: This table uses the future baseline with climate change and population growth and the specification with amenity externalities ($\eta_W = 0.02$, $\eta_N = 0.06$, $\alpha_P = 0$). Values are millions of dollars in present value. Panel A reports the welfare cost of wildfire risk (WCW). Panels B and C report changes in WCW relative to the Panel A level. Positive values denote higher WCW; negative values denote lower WCW. A negative Panel A value means that wildfire risk benefits that group in equilibrium. Aggregate distortion counterfactuals apply uniform changes to insurance pricing or housing capacity across space. Policy counterfactuals use cost-based insurance pricing and targeted up-zoning within Transit Priority Areas (TPAs).

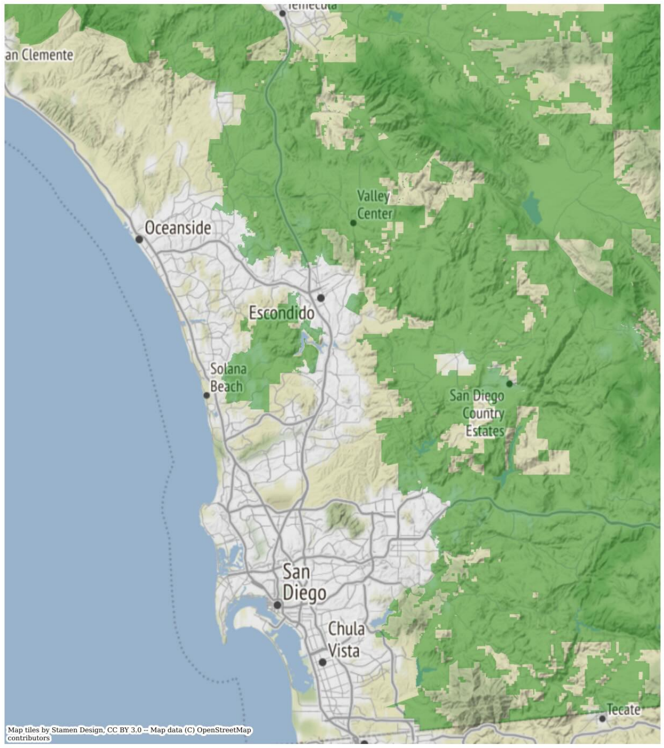
Table A.15: Welfare cost of wildfire risk and counterfactual changes (Endogenous wildfires)

	(1) Workers	(2) Safe LO	(3) Risky LO	(4) All LO	(5) Total
Panel A. Baseline WCW level					
Baseline	15,511	-6,206	8,271	2,065	17,576
Panel B. Aggregate distortion counterfactuals: change in WCW					
Uniform insurance change ($\Delta \ln \tau = 10\%$)	139	-309	318	9	148
Uniform building change ($\Delta \ln \bar{H}_i = 10\%$)	-749	657	261	918	169
Joint uniform change	-624	360	583	944	320
Interaction (joint - separate)	-13	11	5	16	3
Panel C. Policy counterfactuals: change in WCW					
Cost-based insurance ($\Delta\tau = R - \tau$)	420	-906	1,016	110	530
TPA up-zoning ($\Delta \ln \bar{H}_{TPA} = 15\%$)	-452	337	144	482	29
Joint targeted reform	-57	-550	1,170	620	564
Interaction (joint - separate)	-24	19	10	29	5

Notes: This table uses the baseline no-amenity specification with endogenous wildfires ($\eta_W = 0$, $\eta_N = 0$, α_P estimated). Values are millions of dollars in present value. Panel A reports the welfare cost of wildfire risk (WCW). Panels B and C report changes in WCW relative to the Panel A level. Positive values denote higher WCW; negative values denote lower WCW. A negative Panel A value means that wildfire risk benefits that group in equilibrium. Aggregate distortion counterfactuals apply uniform changes to insurance pricing or housing capacity across space. Policy counterfactuals use cost-based insurance pricing and targeted up-zoning within Transit Priority Areas (TPAs).

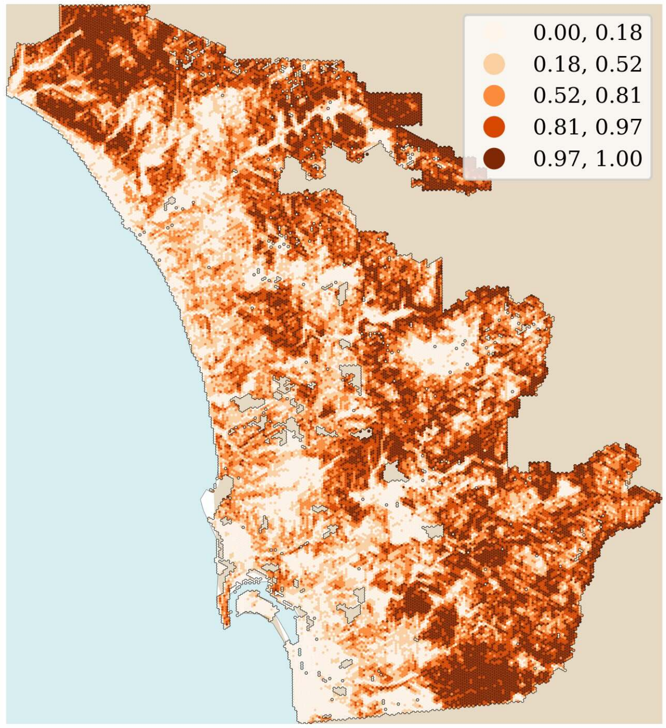
A.3 Plots and maps

Figure A.1: The San Diego metropolitan area



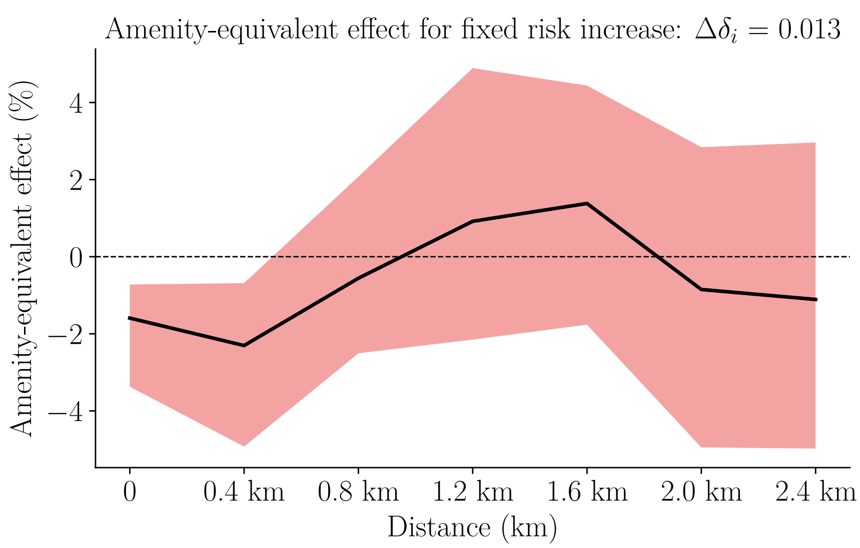
Notes: The areas shaded in green are protected land owned by the State of California or the federal government. The San Diego metropolitan area is contained in the county of San Diego, located in the southwestern corner of California. As of the 2020 census, its population of 3.3 million makes it the second most populous county in California and the fifth most populous in the country. To the south, the metropolitan area is limited by the U.S.–Mexico border, and to the northwest, north of Oceanside, by land owned by the U.S. military. From east to west, the San Diego metropolitan area stretches from the Pacific Ocean to the Peninsular Ranges, beyond which is the Colorado Desert.

Figure A.2: Fraction of area of steep slope (greater than 15%)



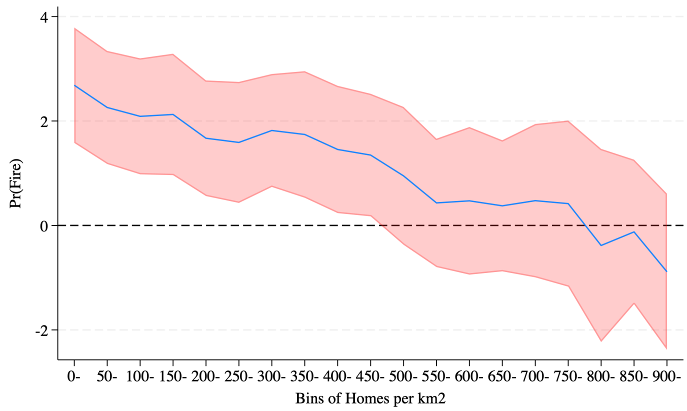
Notes: Choropleth maps of the fraction of resolution-9 regular hexagons that have slopes over 15%. The source of the slope map is the LUEG-GIS Service, Planning & Development Services, County of San Diego.

Figure A.3: Marginal Impact of Greater Burn Probability on Amenities, by Distance



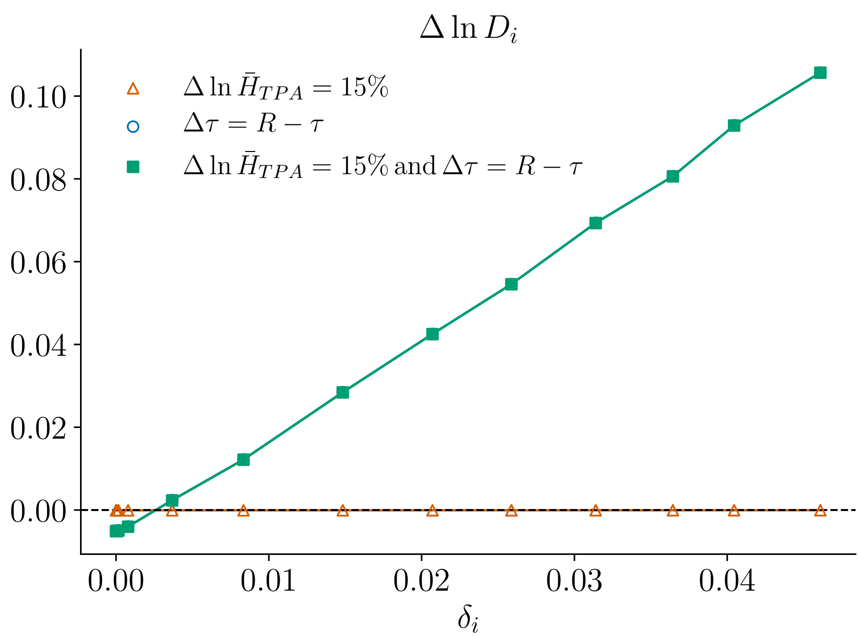
Notes: Marginal effect of a one standard deviation (0.013) increase in annual burn probability at different distances from a resolution-9 hexagon. The dark line runs through the point estimates and the red shaded area indicates 95% confidence intervals. Except for the lag structure, the specification and sample restrictions are identical to the ones in Column 3 of Table 1.

Figure A.4: Link between population density and wildfire burn probability



Notes: flexible version of the specification of column 4 of Table A.9, where I replace the right-hand-side variable log(home density) with equally-spaced bins of home density.

Figure A.5: Effects of targeted policy counterfactuals on housing development costs



Note: Binned scatter plots of simulated counterfactual changes (y-axis) vs. annual burn probabilities (x-axis).

B Data Appendix

B.1 Parcel data and market-value assessments

The parcel records I use in the main analysis came from SANDAG and report housing units, square footage, and assessed values for each plot of land in San Diego County. I combined these records with 18 years of parcel transactions data, from 2001 to 2018, to recover parcel-level market-value assessments. The transactions came from the Zillow Transaction and Assessment Dataset (ZTRAX). This adjustment is necessary because raw assessed values are shaped by California's reassessment rules and therefore need not equal contemporaneous market prices. The goal of the procedure is to preserve the level information in observed sales while using the broader transaction sample to update non-transacted parcels over time.

Let n index transactions, let $a(n)$ denote the parcel sold in transaction n, and let $y(n)$ denote the calendar year of that sale. Let v_n be the observed transaction price per square foot. For each parcel a, let z_a collect the characteristics used to form comparisons across properties: indicators for framing type, high-quality construction, complex shape, bedroom categories, view, pool, and ZIP code. I estimate the year-specific hedonic relationship

$$\ln v_n = z'_{a(n)} \kappa_{y(n)} + u_n,$$

which allows the implicit value of these characteristics to vary freely over time. The fitted values imply a predicted market price per square foot for every parcel-year pair,

$$\widehat{v}_{a,y} \equiv \exp\left(z'_a \widehat{\kappa}_y\right).$$

Next, for each parcel a and year y, let $s(a, y)$ be the most recent year at or before y in which parcel a sells in the transaction data, when such a sale exists. I define the market-value assessment $M_{a,y}$ as

$$\ln M_{a,y} = \begin{cases} \ln v^{obs}_{a,y} & \text{if parcel } a \text{ sells in year } y \\ \ln v^{obs}_{a,s(a,y)} + \ln \widehat{v}_{a,y} - \ln \widehat{v}_{a,s(a,y)} & \text{if } s(a,y) < y \\ \ln \widehat{v}_{a,y} & \text{if parcel } a \text{ never sells in the sample.} \end{cases}$$

Therefore, when a parcel sells I use the transaction price directly; between sales I update the level of the last observed sale with the change implied by the estimated hedonic schedule; and for parcels without any observed sale I use the hedonic prediction. This construction mimics an assessor who combines the most recent sale of a property with information from comparable sales in the same year.

In the main analysis I overlay parcels on the hexagonal grid and aggregate these parcel-level market-value assessments to the hexagon-year level using the median value per square foot. I then convert the resulting housing values into rent measures using ACS rent-to-value ratios. These hexagon-level rent measures are the housing-price inputs used in the estimation of location demand.

B.2 Insurance Data

I obtained premiums and units exposed to loss by ZIP code in California from the California Department of Insurance (CDI). I obtained data from two databases. First, the Community Service Statement (CSS) database contains yearly data from 2009 to 2018 on premiums and units exposed to loss by company and policy type within each ZIP code. Second, the Personal Property Experience (PPE) database contains the amount of coverage for structures, the amount of coverage for contents, and the number of units covered by ZIP code. The available sample covers years 2009, 2011, 2013, 2015, and 2017 to 2019.

To arrive at the premium rates per dollar of coverage used in estimation I start by calculating average premiums per ZIP code using the CSS data. Then I match the data to the PPE dataset and for the matched years divide the average premium by the average dollar amount of insurance provided under Coverage A (Structure) obtained from the PPE. I restrict the data to homeowner (HO) policies.

C Model Details

C.1 Workers

Workers are ex-ante identical and make the following choices.

1. Choose whether to live in the modeled city (the San Diego metropolitan area) or in the rest of the country
2. Choose residence i
3. Choose commuting destination J
4. Choose housing space and consumption of tradable goods

Utility is Cobb-Douglas in housing space and the consumption of a freely tradable good. The expected indirect utility of worker ι living in the city is

$$\mathcal{V} \equiv \mathbb{E}_b \left[\max_i \mathbb{E}_e \left[\max_J \max_{H,C} B_i b_i(\iota) \left(\frac{C}{\beta}\right)^{\beta} \left(\frac{H}{1-\beta}\right)^{1-\beta} \right] \right]$$

subject to the ex-post budget constraint

$$C + Q_i H \leq \frac{W_J E_J e_J(\iota)}{\gamma_{iJ}} \equiv Y_{iJ}(\iota)$$

where $b_i(\iota)$ is distributed Fréchet with shape ε and mean 1 and $e_J(\iota)$ is distributed Fréchet with shape θ and mean 1, mutually iid. The scalar $b_i(\iota)B_i$ measures the residential appeal (i.e., the amenity value) of a hexagon. The scalar $e_J(\iota)E_J$ measures total effective labor units; it captures differences in the efficiency of the unit of labor endowment that the household supplies inelastically. The variable γ_{iJ} captures the cost of commuting between residential hexagon i and workplace tract J.

Workers have heterogeneous preferences over the homes offered by landowners $\ell \in (0, 1)$ in location i. The value of home ℓ to worker ι is given by

$$\ln \omega_i(\ell) + (1-\zeta)\ln q_i(\ell) + \epsilon(\ell,\iota), \tag{16}$$

where $\omega_i(\ell)$ is a preference shifter common across workers, $\zeta > 1$ is a parameter, $q_i(\ell)$ is the rent price of home ℓ, and $\epsilon(\ell,\iota)$ is an idiosyncratic preference shock.

C.1.1 Location and consumption choices

Housing choice. Assuming that the idiosyncratic shock $\epsilon(\ell,\iota)$ is drawn from an i.i.d Gumbel distribution, the probability density function of choosing ℓ is

$$s_i(\ell) \quad = \quad \omega_i(\ell)\left(\frac{q_i(\ell)}{Q_i}\right)^{1-\zeta},$$

where I defined $Q_i \equiv \left(\int_0^1 \omega_i(\ell)\,(q_i(\ell))^{1-\zeta}\,d\ell\right)^{\frac{1}{1-\zeta}}$. The demand for housing space in ℓ is then $h_i(\ell) = \frac{s_i(\ell)Q_iH_i}{q_i(\ell)L_i} = \omega_i(\ell)\frac{H_i}{L_i}\left(\frac{q_i(\ell)}{Q_i}\right)^{-\zeta}$. Given the lot-specific demands, we derive the quantity aggregator over the observed demands:

$$H_i \quad = \quad L_i\left(\int_0^1 (\omega_i(\ell))^{\frac{1}{\zeta}}\,(h_i(\ell))^{\frac{\zeta-1}{\zeta}}\,d\ell\right)^{\frac{\zeta}{\zeta-1}}.$$

Consumption choice. Solving backwards, optimal consumption of the tradable good and housing (before choosing a home ℓ) are given by $c_{iJ}(\iota) = \beta Y_{iJ}(\iota)$ and $h_{iJ}(\iota) = (1-\beta)\,Y_{iJ}(\iota)/Q_i$ so the problem becomes

$$\mathcal{V} = \mathbb{E}_b\left[\max_i\ \mathbb{E}_e\left[\max_J\ B_i b_i(\iota)\frac{Y_{iJ}(\iota)}{Q_i^{1-\beta}}\right]\right].$$

Commuting choice. Because of the i.i.d. assumption, the commuting choice problem is equivalent to choosing the work location with the highest effective income, $\mathbb{E}_e\left[\max_J\ Y_{iJ}(\iota)\right]$:

$$\mathcal{V} = \mathbb{E}_b\left[\max_i\ B_i b_i(\iota)\frac{\mathbb{E}_e\left[\max_J\ Y_{iJ}(\iota)\right]}{Q_i^{1-\beta}}\right].$$

Given the distributional assumptions on labor productivities, the choice probability is

$$\begin{aligned}\lambda_{J|i} \quad &\equiv \quad \Pr\left[J = \arg\max_{J'}\ \frac{W_J E_J e_J(\iota)}{\gamma_{iJ}}\right] \\ &= \quad \frac{(W_J E_J/\gamma_{iJ})^{\theta}}{\sum_{J'}(W_{J'}E_{J'}/\gamma_{iJ'})^{\theta}}\end{aligned} \tag{17}$$

and we can define the expected income as

$$\begin{aligned}\mathbb{W}_i \quad &\equiv \quad \mathbb{E}_e\left[\max_J\ Y_{iJ}(\iota)\right] \\ &= \quad \left[\sum_J (W_J E_J/\gamma_{iJ})^{\theta}\right]^{\frac{1}{\theta}}.\end{aligned}$$

The problem then becomes:

$$\mathcal{V} = \mathbb{E}_b\left[\max_i\ B_i b_i(\iota)\frac{\mathbb{W}_i}{Q_i^{1-\beta}}\right].$$

Residential choice. The residential choice probabilities conditional on living in the city are

$$\begin{aligned}\lambda_i &\equiv \Pr\left[i = \arg\max_{i'} B_{i'} \frac{\mathbb{W}_{i'}}{Q_{i'}^{1-\beta}} b_{i'}(\iota)\right] \\ &= \frac{\left(B_i \mathbb{W}_i Q_i^{\beta-1}\right)^{\varepsilon}}{\sum_{i'}\left(B_{i'} \mathbb{W}_{i'} Q_{i'}^{\beta-1}\right)^{\varepsilon}}.\end{aligned}$$

The expected utility of living in the city is

$$\mathcal{V} = \left[\sum_i \left(B_i \mathbb{W}_i Q_i^{\beta-1}\right)^{\varepsilon}\right]^{\frac{1}{\varepsilon}}.$$

City choice. Workers first choose whether to live in the city (i.e., the San Diego metropolitan area) and the rest of the country. The rest of the country is the outside option and offers mean utility $\mathcal{U}$. Living in the city offers expected indirect utility $\mathcal{V}$. I also assume that workers have idiosyncratic preferences for the city given by $z^{city}(\iota)$ and $z^{out}(\iota)$, i.i.d. type II extreme value with shape $\varepsilon^C > 1$ and mean 1. Under these assumptions, the number of workers who choose to live in the city, N, solves

$$\frac{N}{N^* - N} = \left(\frac{\mathcal{V}}{\mathcal{U}}\right)^{\varepsilon^C},$$

where N^* is the (exogenous) total population in the country.

Housing demand. The Cobb-Douglas utility between consumption and housing implies that the expected (before choosing place of work) housing expenditures of the workers living in i are $Q_i H_i = (1-\beta)\,\mathbb{W}_i N_i$.

C.1.2 Amenities

Amenities have endogenous and exogenous determinants. Specifically,

$$B_i = \frac{b_i}{\varphi_i^B} \underbrace{\left(\mathbb{W}_{I(i)}\right)^{\eta^W} \left(\frac{N_{I(i)}}{L_{I(i)}}\right)^{-\eta^N}}_{\text{endogenous}},$$

where φ_i^B captures expected damages from wildfires, the parameter η^W is the elasticity of amenity value with respect to average income, and the parameter η^N is the elasticity of amenity value with respect to population density. The index $I(i)$ maps hexagon i to its tract I.

I assume a functional form for the amenity damages: $\varphi_i^B = \exp\left(\varphi^B \delta_i\right)$. The interpretation of φ^B is the marginal willingness to pay for a reduction in burn probability as a fraction of income. Or $\varphi^B/(1-\beta)$ can be interpreted as the marginal willingness to pay for a reduction in burn probability in terms of an increase in rents.

C.2 Production

The final consumption good is tradable and produced under conditions of perfect competition and constant returns to scale. The technology uses labor N^y and land L^y as input and is Cobb-

Douglas $A_J (N^y)^\alpha (L^y)^{1-\alpha}$ with parameter $\alpha \in (0,1)$ and Hicks-neutral productivity A_J that is specific to a location J. Cost minimization requires that wages equal marginal products:

$$W_J = \alpha A_J \left(\frac{L_J^y}{N_J^y} \right)^{1-\alpha}.$$

C.3 Landowners

The following elements characterize the problem of landowners.

- Preferences: landowners are risk averse with CARA (constant absolute risk aversion) preferences represented by the utility function $U(C) = 1 - \exp(-\sigma C)$, with parameter $\sigma > 0$.
- Endowment and heterogeneity: each landowner, indexed by $\ell \in (0,1)$, has one unit of the L_i land area available in location i. The landowners within a location are uniform with the exception of a demand shock denoted by $\omega_i(\ell)$. This demand shock implies that housing space in different lots ℓ is only imperfectly substitutable from the perspective of renters. I assume that these demand shocks are drawn independently and identically (i.i.d.) from distribution G with unit mean and finite variance: $\mathbb{E}_\omega[\omega] = 1$, $\mathbb{E}_\omega[\omega^2] < \infty$.
- Timing: landowners first choose housing space $h_i(\ell)$ and rents $q_i(\ell)$ under conditions of monopolistic competition, then choose insurance coverage, then property damages are realized, and finally landowners consume the tradable good with their rental income net of damages and insurance.
- Damages: there are two types of independent insurable risks to property, wildfire damages and a background (non-wildfire) risk.
  - When a destructive wildfire happens (with probability $\rho_i \equiv \delta_i \times \text{FLEP4}_i$), the landowner suffers damages φ^H per unit of housing built. The more housing is built, the larger the damages. Wildfire damages are offset by insurance coverage $x_i(\ell)$, purchased at a premium rate p_i.
  - The background risk (or "other" risk, henceforth) captures plumbing failures, theft, hail, small non-wildfire fires, etc.—perils to any house in the city, even far from the wildland. Background risks incur damages of $\varphi^o h_i(\ell)$, happen with probability ρ^o, and insurance coverage $x_i^o(\ell)$ can be purchased at a premium rate of p^o.
- Technology and building constraints: landowners produce housing at a constant development cost d_i per unit. There is a maximum allowed per-lot capacity given by $\bar{h}_i$, dictated by exogenous regulations.

We solve the problem backwards.

C.3.1 Insurance choice

Omitting the lot indexing (ℓ) for convenience, ex-post consumption as a function of insurance coverages x and x^o is

$$C\left(x, x^o, n_i, n_i^o\right) \;=\; \left(q-d\right)h - \left(p_i x + p^o x^o\right) + \left[n_i^o\left(x^o - \varphi^o h\right) + n_i\left(x_i - \varphi^H h\right)\right],$$

where n_i and n^o are event indicators for wildfire and other perils, respectively. The first term $(q-d)\,h$ is pre-insurance profits. The second term $(p_i x + p^o x^o)$ collects insurance costs. The last term isolates the random part of consumption, coming from the damages net of insurance coverage.

Taking housing space h and rents q as given, the problem is to choose insurance coverages x and x^o at prices p_i and p^o to maximize expected utility:

$$\mathbb{E}_\rho[U] \equiv \max_{x,\,x^o} \quad 1 - \mathbb{E}_\rho\left[e^{-\sigma C\left(x, x^o, n_i, n_i^o\right)}\right],$$

where $\mathbb{E}_\rho$ denotes the expectation over property damages. The first order condition implies insurance coverage demands

$$\begin{aligned} x_i &= \varphi^H h + \frac{1}{\sigma}\ln\left(\frac{\rho_i}{1-\rho_i}\frac{1-p_i}{p_i}\right), \text{ and} \\ x_i^o &= \varphi^o h + \frac{1}{\sigma}\ln\left(\frac{\rho^o}{1-\rho^o}\frac{1-p^o}{p^o}\right), \end{aligned}$$

where we used the independence assumption.

Plugging in the coverage demands we obtain expected utility under optimal coverage choices, which after some manipulation becomes:

$$\mathbb{E}_\rho\left[U_i\left(q,h\right)\right] = 1 - e^{-\sigma\pi_i(q,h)}\,\Omega(\rho^o, p^o)\,\Omega(\rho_i, p_i),$$

where

$$\pi_i(q,h) \equiv \left(q - D_i\right)h$$

is the rental profit function,

$$D_i \equiv d_i + p_i\varphi^H + p^o\varphi^o$$

is the effective per-unit development cost including insurance; and

$$\Omega(\rho, p) \equiv \left(\frac{\rho}{p}\right)^p\left(\frac{1-\rho}{1-p}\right)^{1-p}$$

is a function that captures the utility cost of insurance premium distortions.

Before moving on to solve for the building and pricing decisions, I re-state the landowner's objective as a certainty equivalent consumption or profit. Certainty equivalent profits $\mathcal{C}_i$ are implicitly defined as $U\left(\mathcal{C}_i\right) = \mathbb{E}_\rho\left[U_i\left(q,h\right)\right]$. Solving for $\mathcal{C}_i$ we obtain:

$$\mathcal{C}_i(q,h) = \pi_i(q,h) - \frac{1}{\sigma}\ln\Omega^o - \frac{1}{\sigma}\ln\Omega_i,$$

where $\Omega^o \equiv \Omega(\rho^o, p^o)$ and $\Omega_i \equiv \Omega(\rho_i, p_i)$.

C.3.2 Pricing choice

Price setting. Each landowner ℓ then chooses housing space and prices solving the following problem:

$$\begin{aligned} h_i(\ell), q_i(\ell) &= \arg\max_{h,q} \mathcal{C}_i(q,h) \\ &= \arg\max_{h,q} \pi_i(h,q) \\ \text{subject to} & \\ h &\le \bar{h}_i \\ h &= \omega_i(\ell) \frac{H_i}{L_i} \left(\frac{q}{Q_i}\right)^{-\zeta}. \end{aligned}$$

The second equality in the "argmax" holds because the distortion terms Ω are not a function of housing space h and they enter linearly in the certainty equivalent $\mathcal{C}_i$. That is, after solving for insurance choice, the housing choice problem is equivalent to a risk-less problem with an effective marginal cost of D_i. The Lagrangian is (replacing the housing demand h):

$$\mathcal{L}_i(q,\chi) = (q - D_i - \chi)\,\omega_i(\ell) \frac{H_i}{L_i} \left(\frac{q}{Q_i}\right)^{-\zeta} + \chi \bar{h}_i,$$

where χ is the Lagrange multiplier. Optimality requires that the solutions $q_i(\ell)$ and $h_i(\ell)$ satisfy

$$q_i(\ell) = \frac{\zeta}{\zeta-1}\left[D_i + \chi_i(\ell)\right], \tag{18}$$

$$\chi_i(\ell) = \begin{cases} 0 & \text{if } h_i(\ell) < \bar{h}_i \\ \frac{\zeta-1}{\zeta} Q_i \left(\frac{\omega_i(\ell) H_i}{\bar{h}_i L_i}\right)^{\frac{1}{\zeta}} - D_i & \text{if } h_i(\ell) = \bar{h}_i. \end{cases} \tag{19}$$

Equation 18 characterizes the rent-setting behavior of landowners. If the landowner builds housing below the constraint, the multiplier $\chi_i(\ell)$ is zero and the landowner sets rents at a constant markup over marginal costs, $\zeta/(1-\zeta)$. Once building is constrained, however, the landowner raises their markup ($\chi_i(\ell) > 0$) so as to equate the housing demanded to their building capacity.

Profits. Landowner's rental profits are then

$$\pi_i(\ell) = \frac{\frac{\zeta}{\zeta-1}\left[D_i + \chi_i(\ell)\right] - D_i}{\left(\frac{\zeta}{\zeta-1}\left[D_i + \chi_i(\ell)\right]\right)^{\zeta}} \omega_i(\ell) \frac{H_i}{L_i} Q_i^{\zeta}.$$

If the constraint does not bind, $\chi_i(\ell) = 0$ and

$$\pi_i(\ell) = \frac{1}{\zeta-1}\left(\frac{\zeta-1}{\zeta}\right)^{\zeta} D_i^{1-\zeta} \omega_i(\ell) \frac{H_i}{L_i} Q_i^{\zeta}.$$

If the constraint binds, $\chi_i(\ell) > 0$ and

$$\pi_i(\ell) = \bar{h}_i^{\frac{\zeta-1}{\zeta}} \left[\omega_i(\ell) \frac{H_i}{L_i}\right]^{\frac{1}{\zeta}} Q_i - \bar{h}_i D_i.$$

Expected utility under optimally-chosen prices and building is

$$\mathbb{E}_\rho\left[U_i(\ell)\right] \equiv \max_{q,h} \mathbb{E}_\rho\left[U_i(q,h)\right] = 1 - e^{-\sigma \pi_i(\ell)}\, \Omega^o\, \Omega_i,$$

and the corresponding certainty equivalent is

$$\mathcal{C}_i(\ell) = \pi_i(\ell) - \frac{1}{\sigma}\ln\Omega^o - \frac{1}{\sigma}\ln\Omega_i.$$

C.3.3 Aggregate supply

The threshold landowner. Within a location i, landowners only differ in the demand shifter for their home $\omega_i(\ell)$. From the complementary slackness condition (19), the threshold $\bar{\omega}_i$ at which a landowner becomes constrained satisfies

$$\bar{\omega}_i = \frac{\bar{h}_i L_i}{H_i}\left(\frac{\zeta}{\zeta-1}\frac{D_i}{Q_i}\right)^{\zeta}.$$

For landowners with $\omega_i(\ell) < \bar{\omega}_i$ the building constraint does not bind, and for landowners $\omega_i(\ell) \geq \bar{\omega}_i$ the building constraint binds.

Total housing output and buildup. For constrained landowners the level of output $h_i(\ell)$ is equal to the cap $\bar{h}_i$. For unconstrained landowners with $h_i(\ell) < \bar{h}_i$, we have that using the demand function

$$\frac{h_i(\ell)}{\bar{h}_i} = \omega_i(\ell)\frac{H_i}{\bar{h}_i L_i}\left(\frac{q_i(\ell)}{Q_i}\right)^{-\zeta},$$

and then using the optimality condition for unconstrained landowners $q_i(\ell) = \frac{\zeta}{\zeta-1}D_i$ and replacing the definition of the threshold $\bar{\omega}_i$ we obtain

$$\frac{h_i(\ell)}{\bar{h}_i} = \frac{\omega_i(\ell)}{\bar{\omega}_i}.$$

Therefore, landowner's level of output $h_i(\ell)$ is proportional to their idiosyncratic demand shock $\omega_i(\ell)$ within the cross-section of unconstrained landowners. Because the integral over ℓ is a lot-level average, multiplying the CES term by L_i converts it into total housing in location i. We then replace $h_i(\ell) = \bar{h}_i\omega_i(\ell)/\bar{\omega}_i$ into the demand aggregator to obtain total housing in i:

$$H_i = H\left(\bar{h}_i, \bar{\omega}_i\right) = \bar{h}_i L_i \underbrace{\left(\bar{\omega}_i^{-\frac{\zeta-1}{\zeta}}\int_0^{\bar{\omega}_i}\omega dG(\omega) + \int_{\bar{\omega}_i}^{\infty}\omega^{\frac{1}{\zeta}}dG(\omega)\right)^{\frac{\zeta}{\zeta-1}}}_{\equiv\mathcal{H}(\bar{\omega}_i)}.$$

The total housing cap in i is defined as

$$\begin{aligned}\bar{H}_i &\equiv \lim_{\bar{\omega}_i\to 0} H\left(\bar{h}_i, \bar{\omega}_i\right) \\ &= \bar{h}_i L_i\left(\int_0^{\infty}\omega^{\frac{1}{\zeta}}dG(\omega)\right)^{\frac{\zeta}{\zeta-1}},\end{aligned}$$

which is only a function of the building constraint ($\bar{H}_i = \bar{H}(\bar{h}_i)$). The total buildup rate, defined as $u_i \equiv H_i/\bar{H}_i$, is then

$$u_i = u(\bar{\omega}_i) = \left(\frac{\bar{\omega}_i^{-\frac{\zeta-1}{\zeta}}\int_0^{\bar{\omega}_i}\omega dG(\omega) + \int_{\bar{\omega}_i}^{\infty}\omega^{\frac{1}{\zeta}}dG(\omega)}{\int_0^{\infty}\omega^{\frac{1}{\zeta}}dG(\omega)}\right)^{\frac{\zeta}{\zeta-1}}.$$

The buildup rate is only a function of $\bar{\omega}_i$ and is strictly decreasing, $u'(\bar{\omega}_i) < 0$. Moreover, $\lim_{\bar{\omega}\to\infty} u(\bar{\omega}) = 0$ and $\lim_{\bar{\omega}\to 0} u(\bar{\omega}) = 1$ so $u_i \in [0,1]$.

The supply curve. Replacing the optimal price setting conditions into the price index $Q_i = \left(\int_0^1 \omega_i(\ell)(q_i(\ell))^{1-\zeta} d\ell\right)^{\frac{1}{1-\zeta}}$ we obtain the inverse supply curve:

$$Q_i = \mathcal{M}(\bar{\omega}_i)\ D_i,$$

where the markup $\mathcal{M}$ is defined as

$$\mathcal{M}(\bar{\omega}_i) \equiv \frac{\zeta}{\zeta-1}\left(\int_0^{\bar{\omega}_i} \omega dG(\omega) + \bar{\omega}_i^{\frac{\zeta-1}{\zeta}} \int_{\bar{\omega}_i}^{\infty} \omega^{\frac{1}{\zeta}} dG(\omega)\right)^{\frac{1}{1-\zeta}}.$$

The markup is greater than one ($\mathcal{M} \geq \frac{\zeta}{\zeta-1} > 1$) and strictly increasing ($\mathcal{M}' > 0$). As we approach a situation where no landowners are constrained, the markup approaches the unrestricted monopolistic competition markup: $\lim_{\bar{\omega}\to\infty} \mathcal{M}(\bar{\omega}) = \frac{\zeta}{\zeta-1}$.

Since there is a one-to-one mapping between the cutoff $\bar{\omega}_i$ and the buildup rate $u_i = H_i/\bar{H}_i$, we can re-write the inverse supply equation in terms of buildup rates:

$$Q_i = \mathcal{M}(u_i)\ D_i.$$

With very low buildup, the markup approaches the unrestricted monopolistic competition markup: $\lim_{u\to 0} \mathcal{M}(u_i) = \frac{\zeta}{\zeta-1}$. When we approach full buildup the markup becomes arbitrarily large: $\lim_{u\to 1} \ln \mathcal{M}(u_i) = \infty$.

The empirical supply curve. For estimation and simulations I am interested in the supply equation in log changes:

$$\Delta \ln Q_i = \Delta \ln \mathcal{M}(u_i) + \Delta \ln D_i.$$

To make this equation tractable I approximate the changes in markups as follows. First, I use a first order approximation of the markup changes around the initial buildup rate u_i:

$$\Delta \ln \mathcal{M}(u_i) \approx \mu(u_i)\,\Delta \ln u_i = \mu(u_i)\left(\Delta \ln H_i - \Delta \ln \bar{H}_i\right),$$

where $\mu(u_i) \equiv \mathcal{M}'(u_i)\,u_i/\mathcal{M}(u_i)$ is the markup elasticity. Importantly, $\mu(u_i)$ is the elasticity of the markup rather than the markup level itself, so the theoretical restriction is positivity, not that $\mu(u_i)$ exceed one; values $\mu(u_i) \in (0,1)$ are therefore admissible and correspond to relatively elastic local housing supply. Second, I re-parametrize the markup elasticity in terms of log buildup. Let $\tilde{\mu}(x) \equiv \mu(e^x)$, where $x = \ln u$. I then use a first order approximation around the average log buildup $\overline{\ln u}$:

$$\tilde{\mu}(\ln u_i) \approx \underbrace{\tilde{\mu}\left(\overline{\ln u}\right)}_{\equiv \mu_H} + \underbrace{\tilde{\mu}'\left(\overline{\ln u}\right)}_{\equiv \mu_U}\left(\ln u_i - \overline{\ln u}\right).$$

Substituting these expressions into the supply function we arrive at

$$\Delta \ln Q_i = \underbrace{\left[\mu_H + \mu_U\left(\ln u_i - \overline{\ln u}\right)\right]}_{\equiv \mu_i}\left(\Delta \ln H_i - \Delta \ln \bar{H}_i\right) + \Delta \ln D_i.$$

The first coefficient of the markup elasticity $\mu_H > 0$ must be positive and captures the markup elasticity at average log buildup. The second coefficient μ_U captures how the markup elasticity varies with log buildup. The supply curve is convex when that coefficient is positive, $\mu_U > 0$. That means that an increase in allowed building $\Delta \ln \bar{H}_i$ due to, for example, an up-zoning policy will decrease prices more in locations where the baseline buildup rate u_i is higher.

C.3.4 Aggregate certainty-equivalent profits

Total profits in location i are obtained by integrating over the normalized lot distribution and multiplying by L_i:

$$\Pi_i = L_i \int_0^1 \pi_i(\ell) d\ell = L_i \left[\int_0^1 q_i(\ell) h_i(\ell) d\ell \right] - L_i \left[\int_0^1 h_i(\ell) d\ell \right] D_i.$$

Aggregate revenues are given by $L_i \int_0^1 q_i(\ell) h_i(\ell) d\ell = Q_i H_i$. Exact aggregate costs are $D_i L_i \int_0^1 h_i(\ell)\, d\ell = \mathcal{D}_i D_i H_i$, where

$$\mathcal{D}_i \equiv \frac{L_i \int_0^1 h_i(\ell)\, d\ell}{H_i} \geq 1.$$

When the capacity constraint binds, $\mathcal{D}_i$ depends on the endogenous cutoff $\bar{\omega}_i$. For tractability, I abstract from counterfactual changes in $\mathcal{D}_i$ and absorb its baseline level into the units of H_i.[1] Under that approximation, aggregate profits are

$$\Pi_i \approx (Q_i - D_i)\ H_i.$$

Now using the inverse housing supply equation $Q_i = \mathcal{M}(u_i)\ D_i$,

$$\Pi_i \approx \frac{\mathcal{M}(u_i) - 1}{\mathcal{M}(u_i)} Q_i H_i.$$

Therefore, the total certainty-equivalent profits in location i are

$$\mathcal{C}_i \equiv L_i \int_0^1 \mathcal{C}_i(\ell) d\ell = \Pi_i - \frac{1}{\sigma} \ln(\Omega^o \Omega_i)\, L_i.$$

This is the full landowner certainty-equivalent welfare object. In the empirical welfare calculations below, I quantify its profit component but not the insurance-distortion term, because the CARA parameter σ is not identified and that term does not affect the spatial-equilibrium allocations.

C.4 Insurance supply

There is a regulated insurer that sells coverage to landowners in the city before the realization of property damages, and finances the payouts with the premiums earned. The insurer is restricted to price wildfire risk according to a pricing schedule $p_i = p(\rho_i; \tau)$ given by regulation. By assumption, $p(0; \tau) = 0$, so that $p(\rho_i; \tau)$ captures the additional premium allowed on wildfire risk.

Furthermore, the insurer faces a "revenue requirement condition" that caps its revenues at a constant proportion R of expected costs. The premium rate for other risks, p^o, is thus determined by the pooled self-funding condition:

$$\sum_i (p_i x_i + p^o x_i^o)\, L_i = R \sum_i (\rho_i x_i + \rho^o x_i^o)\, L_i.$$

[1]The CES housing aggregator and its dual price index are defined up to a location-specific multiplicative constant. I choose the baseline units of H_i so that the physical-input requirement per unit of H_i equals one in the reference equilibrium. With binding capacity constraints, the ratio of physical housing to the CES composite varies with $\bar{\omega}_i$, so this mapping is only approximate away from the reference equilibrium. The analytical profit expression therefore abstracts from counterfactual changes in that ratio as a second-order effect.

The left side of the equation is the total premiums earned in the city. The right side of the equation is the total expected payments (i.e., the total cost for a risk-neutral insurer) plus an allowed return of $R-1$ that captures an allowed return on investment and surplus requirements (or "risk load").

If we solve for the non-wildfire premium and plug in the wildfire premium schedule $p_i = p(\rho_i;\tau)$ we obtain:

$$p^o = R\rho^o - (\tau - R)\frac{\sum_i \rho_i x_i L_i}{\sum_i x_i^o L_i}.$$

Whether the wildfire risk pool is self-funded depends on the sign of $\tau - R$. If $\tau < R$, wildfire risk is under-funded and we have $p^o > R\rho^o$ (cross-subsidization). If $\tau = R$, wildfire risk is self-funded and we have $p^o = R\rho^o$ and $p_i = R\rho_i$.

C.5 Equilibrium

C.5.1 Equilibrium conditions

We can express an equilibrium of the model as the set of endogenous variables $\{\lambda_i\}, N, \{Q_i\}$ (residential shares, city size, and rents) that given the fundamentals $\{B_i\}, \{\mathbb{W}_i\}, \{D_i\}, \{\mathcal{U}\}, \left\{\bar{H}_i\right\}, N^*$ solve the following equations:

1. Optimal consumption and residential choice:

$$\lambda_i = \frac{\left(B_i \mathbb{W}_i Q_i^{\beta-1}\right)^{\varepsilon}}{\sum_{i'}\left(B_{i'}\mathbb{W}_{i'}Q_{i'}^{\beta-1}\right)^{\varepsilon}}.$$

2. Optimal city choice:

$$\frac{N}{N^* - N} = \left[\sum_i \left(B_i \mathbb{W}_i Q_i^{\beta-1}\right)^{\varepsilon}\right]^{\frac{\varepsilon^C}{\varepsilon}} \mathcal{U}^{-\varepsilon^C}.$$

3. Housing market clearing:

$$Q_i = (1-\beta)\frac{\mathbb{W}_i \lambda_i N}{H_i},$$
$$Q_i = \mathcal{M}\left(H_i/\bar{H}_i\right) D_i.$$

4. Optimal production choices and labor market clearing:

$$\lambda_{J|i} = \left(\frac{W_J E_J/\gamma_{iJ}}{\mathbb{W}_i}\right)^{\theta},$$

$$W_J = \alpha A_J \left(\frac{L_J^y}{\sum_i \lambda_{J|i}\lambda_i N}\right)^{1-\alpha}.$$

Amenities, incomes, and development costs $\{B_i\}, \{\mathbb{W}_i\}, \{D_i\}$ are further determined as follows.

- Amenities, which are endogenous if $\eta^W \neq 0$ or $\eta^N \neq 0$, are given by

$$B_i = b_i \exp\left(-\varphi^B \delta_i\right)\left(\mathbb{W}_{I(i)}\right)^{\eta^W}\left(\frac{N_{I(i)}}{L_{I(i)}}\right)^{-\eta^N}.$$

- Expected income as a function of labor productivity dispersion and commuting frictions given by

$$\mathbb{W}_i \equiv \left[\sum_J \left(W_J E_J/\gamma_{iJ}\right)^{\theta}\right]^{\frac{1}{\theta}}.$$

- Housing development costs given by

$$D_i = d_i + \varphi^H p_i + \varphi^o p^o,$$

and insurance premiums are a function of destructive wildfire probabilities and coverages:

$$\begin{aligned} p^o &= R\rho^o - \frac{\sum_i \left(p_i - R\rho_i\right) x_i L_i}{\sum_i x_i^o L_i} \\ p_i &= p\left(\rho_i; \tau\right). \end{aligned}$$

C.5.2 Specifying changes in development costs and insurance premiums

Before moving on to defining the equilibrium conditions in changes, here I present the expressions for the counterfactual changes in development productivities and premiums that would result from changes in the model fundamentals.

The counterfactual changes in the development cost $D_i = d_i + \varphi^H p_i + \varphi^o p^o$ are given by

$$\Delta \ln D_i = \ln\left(1 + \frac{\varphi^H \tau \rho_i}{D_i}\frac{\Delta p_i}{p_i} + \frac{\varphi^o p^o}{D_i}\frac{\Delta p^o}{p^o}\right).$$

This expression maps changes in wildfire premiums $p_i = \tau\rho_i$ and non-wildfire premiums p^o to changes in housing development costs. The changes in premiums are weighed by their importance over total unit costs: $\varphi_i^H p_i/D_i$ and $\varphi^o p^o/D_i$.

In the expression above, the changes in non-wildfire premiums are endogenous. I compute $\Delta \ln p^o$ by a first order approximation of the expression given by the self-funding condition. Specifically,

$$\begin{aligned} \Delta \ln p^o &\approx \sum_i \left(\frac{\partial p^o}{\partial p_i}\frac{p_i}{p^o}\right)\Delta \ln p_i + \sum_i \left(\frac{\partial p^o}{\partial \rho_i}\frac{\rho_i}{p^o}\right)\Delta \ln \rho_i + \sum_i \left(\frac{\partial p^o}{\partial x_i}\frac{x_i}{p^o}\right)\Delta \ln x_i \\ &= \varpi^o \sum_i \varpi_i \left(-\Delta \ln p_i + R\frac{\rho_i}{p_i}\Delta \ln \rho_i - \frac{p_i - R\rho_i}{p_i}\Delta \ln x_i\right), \end{aligned}$$

where $\varpi_i \equiv p_i x_i L_i/(\sum_{i'} p_{i'} x_{i'} L_{i'})$ is the share of total premiums accounted by location i, and $\varpi^o \equiv (\sum_i p_i x_i L_i)/(\sum_i p^o x_i^o L_i)$ measures the importance of total wildfire-related premiums relative to total premiums for other risks. Using also the expression for wildfire premiums $p_i = \tau\rho_i$ and approximating changes in coverage with changes in housing space $\Delta \ln x_i \approx \Delta \ln H_i$, the expression simplifies to

$$\Delta \ln p^o \approx \varpi^o \sum_i \varpi_i \left(\frac{R-\tau}{\tau}\left(\Delta \ln \rho_i + \Delta \ln H_i\right) - \Delta \ln \tau\right).$$

C.5.3 Equilibrium in changes

Consider a variable in two equilibriums of the model, an initial one denoted by a and a final one denoted by a'. I define proportional log changes in any given variable a as $\Delta \ln a = \ln a' - \ln a$ and discrete changes as $\Delta a = a' - a$. The equilibrium conditions then imply that the counterfactual changes between equilibria satisfy the following 4 conditions, and the fundamentals change as defined below.

1. Optimal consumption and residential choice:

$$\begin{aligned}
\Delta \ln \lambda_i &= \varepsilon \left(\Delta \ln V_i - \Delta \ln \mathcal{V} \right) \\
\Delta \ln V_i &= \Delta \ln B_i + \Delta \ln \mathbb{W}_i - (1-\beta) \Delta \ln Q_i \\
\Delta \ln \mathcal{V} &= \frac{1}{\varepsilon} \ln \sum_{i'} \lambda_{i'} \exp \left(\varepsilon \Delta \ln V_{i'} \right)
\end{aligned}$$

2. Optimal city choice:

$$\Delta \ln \lambda^C = \varepsilon^C \Delta \ln \mathcal{V} - \ln \left[\left(1 - \lambda^C \right) + \lambda^C \exp \left(\varepsilon^C \Delta \ln \mathcal{V} \right) \right]$$

3. Housing market clearing:

$$\Delta \ln Q_i = \frac{\mu_i}{1+\mu_i} \left(\Delta \ln \mathbb{W}_i + \Delta \ln N_i - \Delta \ln \bar{H}_i \right) + \frac{1}{1+\mu_i} \Delta \ln D_i$$

where $\mu_i = \mu_H + \mu_U (\ln u_i - \overline{\ln u}_{2010}) + \mu_S (slope_i - \overline{slope})$ and $u_i = H_i / \bar{H}_i$ and $\Delta \ln N_i = \Delta \ln \lambda_i + \Delta \ln \lambda^C + \Delta \ln N^*$.

4. Labor market clearing:

$$\Delta \ln W_J = \Delta \ln A_J - (1-\alpha) \ln \left[\sum_I \frac{N_{IJ}}{N_J^w} \exp \left(\Delta \ln \lambda_{J|I} + \Delta \ln N_I \right) \right]$$

where

$$\Delta \ln \lambda_{J|I} = \theta \left(\Delta \ln W_J + \Delta \ln E_J - \Delta \ln \gamma_{IJ} - \Delta \ln \mathbb{W}_I \right)$$

and

$$\Delta \ln N_I = \ln \sum_{i \in I} \frac{N_i}{N_I} \exp \left(\Delta \ln N_i \right)$$

and $\Delta \ln N_i$ is defined as in condition 3 above.

The fundamentals change as follows.

- Amenities:

$$\Delta \ln B_i = \Delta \ln b_i - \varphi^B \Delta \delta_i + \eta^W \Delta \ln \mathbb{W}_{I(i)} - \eta^N \Delta \ln N_{I(i)}.$$

- Income:

$$\begin{aligned}
\Delta \ln \mathbb{W}_I &= \frac{1}{\theta} \ln \sum_J \lambda_{J|I} \exp \left[\theta \left(\Delta \ln W_J + \Delta \ln E_J - \Delta \ln \gamma_{IJ} \right) \right] \\
\Delta \ln \mathbb{W}_i &= \Delta \ln \mathbb{W}_{I(i)} - \Delta \ln \gamma_i
\end{aligned}$$

- Development costs:

$$\Delta \ln D_i = \ln \left(1 + \frac{\varphi^H \tau \rho_i}{D_i} \frac{\Delta p_i}{p_i} + \frac{\varphi^o p^o}{D_i} \frac{\Delta p^o}{p^o} \right),$$

where $p_i = \tau \rho_i$ and $D_i = d_i + \varphi^H \tau \rho_i + \varphi^o p^o$.

- Insurance premiums:

$$\Delta \ln p^o = \varpi^o \sum_i \varpi_i \left((R/\tau - 1) (\Delta \ln \rho_i + \Delta \ln H_i) - \Delta \ln \tau \right).$$

C.6 Welfare changes

In this section I derive income-equivalent welfare measures for workers and landowners, so I can aggregate and compare them in the same units.

Workers. I report a utilitarian welfare measure for workers that focuses on individuals who reside in the city in the baseline equilibrium. As shown before, $\Delta \ln \mathcal{V}$ measures the change in the expected utility of living in the city between the counterfactual and the baseline. Because idiosyncratic taste shocks are i.i.d. and workers are ex-ante identical in the location choice problem, all baseline city residents experience the same expected utility change $\Delta \ln \mathcal{V}$. Moreover, $\Delta \ln \mathcal{V}$ has a direct wage-equivalent interpretation: it is the proportional change in all city wages in the baseline equilibrium that would generate the same change in expected utility as the counterfactual.

To derive a monetary-equivalent total welfare change we can multiply $\Delta \ln \mathcal{V}$ by the baseline aggregate (commuting-adjusted) labor income of baseline city residents: $\sum_i \mathbb{W}_i N_i$. For direct comparability with the welfare of landowners, we can use the housing-expenditure identity ($Q_i H_i = (1-\beta)\mathbb{W}_i N_i$) to write this purely in terms of baseline rent payments:

$$\Delta \mathcal{W}^W \equiv \Delta \ln \mathcal{V} \frac{1}{1-\beta} \sum_i Q_i H_i.$$

Landowners. I consider the change in profits. A first order log-linear approximation to the change in profits is given by

$$\Delta \ln \Pi_i \approx \frac{1}{\mathcal{M}_i - 1} \Delta \ln \mathcal{M}_i + \Delta \ln Q_i + \Delta \ln H_i.$$

The markup levels are not identified, so instead I approximate them with the constant-markup lower bound $\lim_{u \to 0} \mathcal{M}(u_i) = \zeta/(\zeta - 1)$. Under that approximation, and again using the approximation for changes in markups developed above, the expression simplifies to

$$\Delta \ln \Pi_i \approx (\zeta - 1)\mu_i \left(\Delta \ln H_i - \Delta \ln \bar{H}_i \right) + \Delta \ln Q_i + \Delta \ln H_i.$$

To aggregate these changes into a utilitarian welfare measure for landowners I weigh them by baseline profits. Because profit levels require markup levels, which I do not identify, I again use the constant-markup lower bound ($\mathcal{M} = \zeta/(\zeta - 1)$). This lower bound implies the constant profit share $\Pi_i \approx \frac{1}{\zeta} Q_i H_i$, and therefore the first-order profit-flow change $\frac{1}{\zeta}(Q_i H_i) \Delta \ln \Pi_i$. Since the model implies higher markups in more built-out locations, this approximation likely understates baseline profits, and therefore welfare weights, in safer constrained areas relative to riskier unconstrained areas. The resulting incidence estimates should therefore be interpreted as conservative for landowners in high-markup, more built-out locations. Aggregating across locations, the monetary-equivalent welfare change for landowners is

$$\Delta \mathcal{W}^L \equiv \frac{1}{\zeta} \sum_i (Q_i H_i) \Delta \ln \Pi_i.$$

This statistic captures the general-equilibrium financial incidence of the counterfactual through profits. It does not include the direct certainty-equivalent effect of changes in the insurance wedge Ω_i, which depends on σ and is not identified in the empirical implementation.

The welfare cost of wildfires (WCW). I define the welfare cost of wildfires building on the constructed welfare measures $\Delta\mathcal{W}^W$ and $\Delta\mathcal{W}^L$. The sum of the two is $\Delta\mathcal{W}$. I define

$$WCW(\Delta\delta_i, \mathcal{S}_i) \equiv \Delta\mathcal{W}(\Delta\delta_i, \mathcal{S}_i) - \Delta\mathcal{W}(0, \mathcal{S}_i)$$

for

$$\Delta\delta_i \,:\, \Delta\delta_i \leq 0,\, \Delta\delta_i + \delta_i > 0.$$

The conditions on $\Delta\delta_i$ are forced by definition so WCW is properly defined as a cost, and so the wildfire risk probabilities don't become negative. The object $\mathcal{S}_i$ is a collection of other counterfactual shocks: $\mathcal{S}_i \equiv \{\Delta\tau,\, \Delta\ln\bar{H}_i,\, \Delta\ln N^*\}$

Notice that this definition makes it explicit that there is not a "single" total cost of wildfire risk; it depends how we define the $\Delta\delta_i$. This is because changing to $\delta_i = 0$ is not well defined in the insurance model. In my preferred specification, I bring down burn probabilities to above the 1% percentile: $\Delta\delta_i = \min\{\delta_{1\%} - \delta_i, 0\}$.

D Theoretical implications

In this section I derive a set of comparative statics that highlight the main economic forces at play in the model.

D.1 Simplified equilibrium

To aid expositional clarity I re-write the equilibrium of the model assuming that there is no migration in or out of the city, no amenity externalities ($\eta^W = \eta^N = 0$), exogenous insurance premiums, and exogenous wages ($\alpha = 1$). Total differentiation of the equilibrium conditions yields:

$$\begin{aligned} d\ln N_i &= d\ln N + \varepsilon d\ln B_i - \varepsilon(1-\beta)\, d\ln Q_i, \\ d\ln Q_i &= \frac{\mu_i}{1+\mu_i}\left(d\ln N_i - d\ln\bar{H}_i\right) + \frac{1}{1+\mu_i} d\ln D_i. \end{aligned}$$

Consider changes in N and N_i that satisfy the equilibrium. Plugging in $d\ln D_i = d\ln B_i = d\ln\bar{H}_i = 0$ and solving for $d\ln N_i / d\ln N$ yields:

$$\frac{d\ln N_i}{d\ln N} = \frac{1}{1 + \varepsilon(1-\beta)\frac{\mu_i}{1+\mu_i}}.$$

This expression is decreasing in μ_i, so places with higher μ_i (steeper supply) expand less when the overall city grows.

D.2 Up-zoning

Consider a local up-zoning $d\ln \bar{H}_i > 0$. Plugging in $d\ln N = d\ln B_i = d\ln D_i = 0$ we obtain that rents and population changes as follows:

$$\begin{aligned}\frac{d\ln Q_i}{d\ln \bar{H}_i} &= -\frac{\frac{\mu_i}{\mu_i+1}}{1+\varepsilon\left(1-\beta\right)\frac{\mu_i}{1+\mu_i}} < 0, \\ \frac{d\ln N_i}{d\ln \bar{H}_i} &= \frac{\varepsilon\left(1-\beta\right)\frac{\mu_i}{\mu_i+1}}{1+\varepsilon\left(1-\beta\right)\frac{\mu_i}{1+\mu_i}} > 0.\end{aligned}$$

Rents fall when you up-zone, as building capacity increases and markups fall. Population in the up-zoned area increases as lower rents attract more residents. The strength of both effects is governed by how steep is the housing supply curve (the markup elasticity μ_i), the sorting elasticity ε, and the expenditure share on housing $1-\beta$.

D.3 Determinants of risk exposure

Consider changes in N_i, B_i and D_i that satisfy the equilibrium. Plugging in $d\ln N = 0$ yields:

$$d\ln N_i = \varepsilon \frac{1}{1+\varepsilon\left(1-\beta\right)\frac{\mu_i}{1+\mu_i}}\left(d\ln B_i - \frac{1-\beta}{1+\mu_i} d\ln D_i\right)$$

Considering now a marginal change in wildfire risk ($d\delta_i$):

$$\frac{d\ln N_i}{d\delta_i} = \varepsilon \frac{1}{1+\varepsilon\left(1-\beta\right)\frac{\mu_i}{1+\mu_i}}\left(-\varphi^B - \frac{1-\beta}{1+\mu_i}\frac{\varphi^H}{D_i}\frac{dp_i}{d\delta_i}\right)$$

Because insurer-side risk is $\rho_i = \delta_i \times \text{FLEP4}_i$, $dp_i/d\delta_i$ should be interpreted holding local fire intensity fixed. Higher risk reduces population via amenities ($-\varphi^B$), plus via the cost channel if insurance premiums increase with risk ($dp_i/d\delta_i > 0$). If premiums are cross-subsidized such that $dp_i/d\delta_i$ is small or even negative at high risk, the cost channel can reinforce or dampen the amenity channel. A higher local markup elasticity μ_i attenuates this property-channel response, so steeper local housing supply makes the population-risk gradient flatter in absolute value.

E Model quantification

E.1 Estimation of location demand parameters $(\beta, \varepsilon, \varphi^B, \theta, \gamma^D)$

I use hexagon-level regressions to estimate ε and φ^B and bilateral tract-level regressions to estimate θ and γ^D.

Hexagon-level. I estimate ε and φ^B from the following empirical equation, that comes from combining optimal hexagon location choices (2), the specification of amenities (5) in the model, and the separable specification of commuting costs $\gamma_{iJ} = \gamma_i \exp(\gamma^D dist_{I(i)J})$:

$$\ln N_i = -\varepsilon\varphi^B\delta_i - \varepsilon(1-\beta)\ln Q_i - \ln\gamma_i^{\varepsilon} + \xi_{I(i)} + \ln b_i^{\varepsilon},$$

where $\xi_{I(i)}$ is a tract-level fixed effect. In practice, I do this in two steps. To proceed, I need a value for β, which I set so that $1-\beta$ equals the housing expenditure share in the ACS data.

1. First estimate a specification in time changes under the assumption that wildfire risk did not vary significantly between 2010 and 2017:

$$\Delta \ln N_i = -\varepsilon(1-\beta)\Delta \ln Q_i - \Delta \ln \gamma_i^{\varepsilon} + \xi_{I(i)} + \Delta \ln b_i^{\varepsilon}.$$

   I am slightly abusing notation and using the same name for the tract fixed effect, $\xi_{I(i)}$, even though the structural counterpart is not identical. Given the value for β, I recover an estimate for ε. I instrument the 2010-2017 changes in rents $\Delta \ln Q_i$ with a leave-one-out measure of initial surrounding buildup in 2010. Denoting the 2010 buildup rate in hexagon i as $u_i \equiv H_i/\bar{H}_i$, where H_i is 2010 observed housing space and $\bar{H}_i$ is the maximum permitted housing space. For each hexagon i in tract $I(i)$, I define the excluded instrument as the mean buildup rate of the other hexagons in the same tract,

$$\bar{u}_{-i} \equiv \frac{1}{|I(i)|-1} \sum_{j \in I(i),\, j \neq i} u_j.$$

2. Given the estimates ε and β, estimate φ^B from

$$\ln(N_i^{1/\varepsilon} Q_i^{1-\beta}) = -\varphi^B \delta_i - \ln \gamma_i + \xi_{I(i)} + \ln b_i$$

   with 2017 data. I am again abusing notation with the tract fixed effect, for notational simplicity.

Notice that we need to control for hexagon-level determinants of commuting market access, γ_i, beyond the residential tract fixed effects. I do so by including as controls log distances to freeways and to ramps and the interaction of the two.

Tract-level. To estimate θ and γ^D I proceed in two steps:

1. First estimate the following bilateral commuting flow equation following from optimal commuting choices in the model (17) using 2017 data:

$$\ln N_{IJ} = \gamma^{dist} dist_{IJ} + \xi_J + \xi_I + u_{IJ}.$$

2. Given the estimates ζ_J and γ^{dist}, estimate θ from the components of the workplace fixed effect ξ_J implied by the model,

$$\xi_J = \theta \ln W_J + \ln E_J^{\theta}$$

   and use θ to recover the distance disutility as $\gamma^D = -\gamma^{dist}/\theta$.

In step 2, I instrument log workplace wages in 2017 with a destination-specific leave-out market-access predictor of 2010 wages, $\ln \hat{W}_{J,10}$. For each origin-destination pair (I, J), I compute origin I's 2010 commuting mass excluding destination J, $N_{I,-J,10} \equiv \sum_{J' \neq J} N_{IJ',10}$. I then project $\ln W_{J,10}$ on a flexible set of interactions between inverse bilateral distance, $(dist_{IJ}^{-1}, dist_{IJ}^{-2})$, and the leave-out commuting mass,$(\ln N_{I,-J,10}, (\ln N_{I,-J,10})^2)$. The excluded instrument is the average across origins of the fitted values from this bilateral projection. Thus, $\ln \hat{W}_{J,10}$ is a tract-level predictor of workplace wages based on predetermined spatial access to surrounding 2010 commuting demand.

E.2 Calibration of endogenous amenities (η^W, η^N)

In baseline simulations, I set $\eta^W = \eta^N = 0$. This shuts down endogenous amenity feedbacks and isolates the roles of wildfire disamenities, insurance costs, and housing supply frictions when wages are endogenous. In robustness exercises, I use the extension

$$\ln B_i = \ln b_i - \varphi^B \delta_i + \eta^W \ln \mathbb{W}_{I(i)} - \eta^N \ln(N_{I(i)}/L_{I(i)}),$$

where $L_I \equiv \sum_{i \in I} L_i$. I calibrate (η^W, η^N) externally without additional estimation. To discipline magnitudes, I use the mediation evidence in Gyourko and McCulloch (2024) and focus on their all-units estimates, which are the closest empirical counterpart to my model's single housing-service market (without a tenure choice margin). In their preferred mediation comparison, adding income controls on top of race controls attenuates the density disamenity estimate by about 12% for all units. In my notation, that attenuation discipline implies

$$\frac{\eta^W}{\eta^N} = \frac{a}{\left|\frac{\partial \ln \mathbb{W}_I}{\partial \ln(N_I/L_I)}\right|(1-a)}, \quad a = 0.12.$$

I set $|\partial \ln \mathbb{W}_I / \partial \ln (N_I/L_I)| = 0.4$ as a descriptive elasticity in the baseline, which implies $\eta^W/\eta^N \approx 0.34$. This gives a non-arbitrary target for the relative size of the two channels. To discipline the level of η^W, I use Macek (2024): the implied income-capitalization elasticity from doubling-income estimates is about 0.18–0.38, so I use $\eta^W \leq 0.18$ as an upper bound in core runs. Finally, Gyourko and Molloy (2015) informs the sign and ranking prior, for which I impose $\eta^N > \eta^W > 0$. Under these restrictions, the baseline values are $(\eta^W, \eta^N) = (0.02, 0.06)$, which imply that a 10% increase in tract income raises amenities by 0.2%, while a 10% increase in tract density lowers amenities by 0.6%.

E.3 Calibration of housing preferences (ζ)

To parametrize the elasticity of substitution across housing units within a neighborhood ζ, I use the equivalence between a one-level CES aggregator and a multinomial logit specification in which log rent enters utility (as specified in Equation 16). In this formulation, the CES elasticity ζ maps directly to the logit coefficient on log rent $1 - \zeta$. Ouazad and Rancière (2019) use San Francisco Bay area data to estimate this coefficient directly. They obtain a value of -3.027 in a specification using log rents (Appendix Table G) and a value between -0.089 and -0.299 in a specification using log house prices (Table 2). The coefficient on log rent implies a much higher elasticity ($\zeta \approx 4$) than the coefficient on log price ($\zeta \approx 1.1$–1.3), consistent with greater price sensitivity in rental demand. Because I expect mobility and substitution patterns in my setting to lie between these extremes, I adopt a midpoint value of $\zeta = 2.5$ as the baseline.

E.4 Estimation of parameters in insurance demand and supply $(\tau, \varphi^H, p^o\varphi^o)$

I first exploit variation in average premiums and fire coverage to estimate the wildfire risk premium (τ). I then use variation in total premiums and the distribution of housing exposed and not exposed to wildfire risk to estimate the composite parameters $\tau\varphi^H$ and $p^o\varphi^o$. Together with τ, we recover wildfire damages φ^H. Finally, I use these estimates to compute the cost shares and premium shares in the initial equilibrium needed for counterfactuals.

I estimate the destructive wildfire risk insurance premium schedule $p_i = p(\rho_i; \tau) = \tau\rho_i$ using data on premiums and coverage amounts for every ZIP code in California. Specifically, I observe average premiums $\bar{p}^*_{z,t}$ (including both wildfire and non-wildfire perils) for ZIP code z and year t, and a measure of average fire coverage $\bar{x}_{z,t}$. Using the expression for total premiums implied by the model we can write

$$\bar{p}^*_{z,t} = \tau\bar{\rho}_{z,t}\bar{x}_{z,t} + \tau\mathrm{Cov}_z(\{\rho_{i,t}\}, \{x_{i,t}\}) + p^o_t\bar{x}^o_{z,t}.$$

Therefore, given appropriate controls for non-wildfire premiums and for the within-ZIP covariance between destructive wildfire risk and coverage, we can identify τ from a regression of average premiums on the interaction of average wildfire risk and average fire coverage.

I estimate $\tau\varphi^H$ and $p^o\varphi^o$ controlling the magnitude of wildfire and non-wildfire damages to property again using ZIP-code insurance data, but now total instead of average premiums. The model implies that total premiums in a ZIP code $p^*_{z,t}$ will be equal to

$$p^*_{z,t} \quad = \quad (\tau\varphi^H)\sum_{i\in z}\rho_i H_{i,t} + (p^o\varphi^o)\, H_{z,t} + \tilde{\varphi}_z + \tilde{\varphi}_{z,t}.$$

This equation says that an increase in housing space in a ZIP code increases total premiums by $p^o\varphi^o$ if the increase happens in locations within the ZIP code with no wildfire risk ($\rho_i = 0$). If instead it happens in risky locations, total premiums will increase by an additional $\tau\varphi^H$ times the increase in ZIP-code level exposure $\sum_{i\in z}\rho_i H_{i,t}$.

In the model, damages are defined per unit of housing space. However, due to data constraints, in estimation I use the count of housing units in lieu of housing space $H_{i,t}$. As a result, the estimated coefficients should be interpreted as per-unit equivalents of the per-space parameters; formally, the composite term $\tau\varphi^H$ recovers $\tau\tilde{\varphi}^H$ scaled by a risk-weighted average of home sizes, while $p^o\varphi^o$ recovers $p^o\tilde{\varphi}^o$ scaled by an (approximately) unit-weighted average of home sizes. For the counterfactuals, these parameters primarily matter through ratios and cost shares (e.g., the self-funding condition and composite unit costs), so a common scaling by average space per unit largely cancels. Deviations arise if average space per unit varies systematically with wildfire risk within ZIP codes, in which case unit-based exposure is a noisy proxy for space-based exposure. If higher-risk locations tend to have larger homes within ZIP codes, then the measured $\sum_{i\in z}\rho_i H_{i,t}$ understates the model-consistent one, which would tend to inflate the implied per-space wildfire damage equivalent; if risky-area homes are smaller, the bias goes in the opposite direction. Analogous considerations apply to the relative magnitude of wildfire versus non-wildfire damage components if the non-wildfire premium includes a larger per-policy fixed component that does not scale with housing size.

To perform counterfactual simulations, I also require measuring the development cost shares of wildfire and other risks ($\varphi^H p_i/D_i$ and $\varphi^o p^o/D_i$). The challenge is that the (per-period) unit cost of housing development d_i is unknown. To make progress, I note that if the damages (or reconstruction cost) are broadly similar to the upfront development or construction costs, then annualizing the damages provides an estimate for average d_i. Discounting at a rate of 5% over a 50-period horizon (and with no residual value), we have that $\bar{d} \approx \varphi^H\, 0.055$. Then the cost shares are given by

$$\begin{aligned}\frac{\varphi^H p_i}{D_i} &\approx \frac{\tau\varphi^H\rho_i}{(0.055+\tau\rho_i)\varphi^H+\varphi^o p^o}\\ \frac{\varphi^o p^o}{D_i} &\approx \frac{\varphi^o p^o}{(0.055+\tau\rho_i)\varphi^H+\varphi^o p^o},\end{aligned}$$

which are only functions of destructive wildfire risk ρ_i and the estimated parameters τ, φ^H, and $\varphi^o p^o$.

The last piece of data needed for the simulations are the premium shares ϖ^o and ϖ_i entering the self-funding condition. I proceed by approximating the total premiums by their damage component (and ignoring the distortion term): $p_i x_i L_i \approx \tau\rho_i\varphi^H H_i$ and $p^o x_i^o L_i \approx p^o\varphi^o H_i$. Under that approximation, the wildfire premium share becomes the wildfire housing exposure share

$$\varpi_i \approx \frac{\rho_i H_i}{\sum_{i'}\rho_{i'}H_{i'}},$$

and the share of total wildfire to non-wildfire premiums becomes

$$\varpi^o \approx \frac{\tau\varphi^H}{p^o\varphi^o}\sum_i \frac{H_i}{H}\rho_i.$$