# Pollution, Population, and Production: A Structural Analysis of Wildfire Smoke and Spatial Sorting

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**Abstract**

Wildfires in the United States are becoming more frequent and severe, with California bearing the greatest burden. While prior research emphasizes direct damages and health effects, this study examines how wildfire incidents and their smoke influence household migration and firm performance. Exploiting temporal variation in wildfire and smoke exposure from 2011–2023, we combine household-level migration and demographic data with firm-level information on employment, revenue, and survival. Both hazards cause persistent population losses, with smoke having the larger effect: a one–standard-deviation increase in smoke exposure reduces household counts by 0.3–0.4% each year following exposure, whereas comparable wildfire exposure lowers them by about 0.2%. By contrast, smoke exposure has particularly strong effects on older households: those aged 50 and above experience declines exceeding 0.5% in several lags, while younger groups show small, short-run inflows, reflecting differences in preferences toward smoke exposure and likelihood of homeownership. These heterogeneous responses translate into meaningful shifts in neighborhood composition, altering the spatial sorting of households across affected areas. Smoke exposure also leads to sizable and lasting contractions in business activity, reducing firm counts by about one percent per standard deviation, with smaller firms disproportionately affected. To capture the general equilibrium implications of these shifts, we estimate a residential sorting model in which local amenities are endogenously supplied by firms operating within neighborhoods. We find that, on average, households are willing to pay 3.2% of property value to avoid such smoke exposure, rising to 4% among those aged 65 and above. The model highlights that older households are key drivers of local service demand—particularly in health and retail—while education services are least responsive to changes in the older population.

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# 1 Introduction

Climate change has amplified the frequency and intensity of wildfires across the United States, with California experiencing the brunt of these changes (Brown et al., 2023; Jolly et al., 2015; Parks et al., 2018; Westerling et al., 2006). According to the National Interagency Fire Center, the number of acres burned annually by wildfires in the U.S. has grown by roughly 4 percent per year since 1983. In 2020 alone, more than 58,000 fires scorched over 10 million acres (NIFC, 2024). While the destruction of landscapes is highly visible, the less tangible economic and social consequences are immense. In California alone, estimated capital losses from fires total \$27.7 billion, and smoke-related health damages reach \$32.2 billion (Wang et al., 2021). Empirical studies document that wildfire smoke increases hospital admissions (Heft-Neal et al., 2023; Kochi et al., 2016; Moeltner et al., 2013), reduces birth weight (Jones and Berrens, 2021), raises the risk of preterm birth (Heft-Neal et al., 2022), and depresses labor-market earnings (Borgschulte et al., 2024).

Despite this growing evidence on direct damages, much less is known about the long-run economic and demographic adjustments that follow wildfire and smoke exposure. Knittel and Krebs (2024) use county-level migration data to show that smoke increases out-migration within California, while Wang (2024) find that higher-income households are disproportionately likely to move away from wildfire exposure. Yet these studies focus narrowly on smoke, leaving the joint roles of direct wildfire exposure and smoke underexplored and offering little insight into welfare or firm-level effects. Household migration, however, can indirectly influence local amenities provided by firms operating within neighborhoods or cities. Changes in the local population composition may alter the demand for services, thereby affecting firms' entry, exit, and investment decisions. These feedback effects can, in turn, shape the utility of the households that remain, as the availability and quality of amenities evolve with local economic activity. Incorporating a general equilibrium framework that captures these interactions between households and firms allows for a deeper understanding of the mechanisms driving adjustment to environmental shocks and their implications for welfare.

Wildfires and their smoke have significant direct and indirect impacts on firms and households. Directly, wildfires cause infrastructure damage, utility disruptions, and rising insurance costs. Indirectly, smoke leads to labor shortages, revenue losses, and productivity declines as workers and families relocate to avoid prolonged exposure. Although much of the literature emphasizes the immediate destruction caused by wildfires, less attention has been paid to the persistent economic and demographic effects of both wildfire exposure and smoke. This study extends the existing literature by examining how these two related but distinct environmental hazards jointly shape household migration and firm performance in California through the lens of a structural model that enables welfare calculations.

The literature on firm–household dynamics underscores how household decisions and spatial sorting influence firm behavior and local economies. George and Waldfogel (2003) show that firms adapt to changing household preferences, as seen in gentrifying neighborhoods where an influx of young, college-educated households transforms local business composition. Ferreira and Wong (2020) and Qian and Tan (2021) further illustrate how household preferences and firm entry reshape labor markets and housing demand, while Diamond and Gaubert (2022) highlight how spatial sorting exacerbates inequality. Almagro and Domínguez-Iino (2025) examine how households' preferences for amenities influence firm locations, finding that shifts in demand composition can alter local amenity provision. Together, these studies emphasize the interconnectedness of household behavior, firm decisions, and local economic outcomes—providing a foundation for understanding how environmental stressors like wildfires and smoke can disrupt these dynamics.

We fill a key gap- the absence of a general-equilibrium (GE) treatment that jointly models household sorting and firm responses to wildfire and smoke- by studying these hazards in a GE setting. We combine novel household- and firm-level data from 2011-2023 with a structural model that links migration, firm behavior, and welfare. Building on Almagro and Domínguez-Iino (2025), who model endogenous amenities supplied by monopolistically competitive firms within a dynamic residential sorting framework, we adapt their approach to an environmental-risk context by introducing direct and diffuse disamenities- wildfire and smoke that vary across space and time. This framework separates the effects of wildfire and smoke, allows amenities including those produced by firms to respond endogenously to hazard-driven demographic change, and delivers equilibrium-consistent measures of welfare and willingness to pay (WTP). Within this structure, households choose locations based on the geography (census tract), prices, idiosyncratic tastes, local amenities, and environmental quality, while amenities evolve as firm composition responds to local demand. When older or higher-income households relocate away from smoke-affected areas, demand for services such as health care and high-end retail declines, prompting contraction or exit among firms in those sectors; the resulting reduction in local amenities further lowers the attractiveness of these locations for similar households, amplifying selective out-migration. The model captures this feedback loop between household sorting and amenity provision, showing how persistent environmental degradation can generate long-run structural change in both neighborhood demographics and the local service economy.

Guided by a general-equilibrium perspective, we address three research questions in the following order: first, what is the impact of wildfire and smoke exposure on household migration and firm performance (employment, sales, and survival), and are these effects persistent over time? Second, how do migration-induced changes in neighborhood demographic composition (e.g., age, income) map into the sectoral composition of locally supplied amenities through firm entry, exit, and reallocation? Third, what are the distributional welfare consequences of the spatial distribution of wildfire and smoke—we decompose welfare into losses from direct exposure and losses or gains arising from endogenous changes in amenities and how do these effects differ for movers versus stayers?

Wildfire and smoke exposure are constructed from high-resolution environmental datasets and spatially linked to census tracts. The wildfire exposure measure is based on the California Department of Forestry and Fire Protection (CAL FIRE) (2023) California Fire Perimeters dataset, which reports the spatial extent of each wildfire event. For every census tract, we compute the total area burned within one, five, and ten miles of the tract centroid for each year from 2011 to 2023. Smoke exposure is derived from the gridded wildfire smoke data developed by Childs et al. (2022), which estimate daily PM2.5 concentrations attributable to wildfire smoke. Using these data, we calculate annual counts of days with PM2.5 concentrations above 40 $\mu g/m^3$ and annual mean smoke levels at the tract level, capturing both the frequency and intensity of smoke events. By integrating the wildfire perimeters and smoke concentration grids with tract centroids, we produce consistent, annualized measures of wildfire and smoke exposure for each tract and year, which form the foundation of our empirical analysis.

Identification relies on the spatial and temporal variation in wildfire and smoke exposure across California over the 2011-2023 period. Wildfire activity is spatially concentrated and varies substantially from year to year, while smoke exposure is more diffuse and extends well beyond the immediate burn zones. As illustrated in Figure 1, this spatial separation provides quasi-random variation in smoke intensity across regions, including areas with no direct wildfire exposure. This variation allows us to isolate the localized effects of wildfire exposure from the broader, downwind impacts of smoke.

The analysis in this paper proceeds in two parts. First, we estimate a panel regression framework at the census tract level for the years 2011-2023 using continuous measures of both wildfire and smoke exposure. Wildfire exposure is measured as the total area burned within one mile of the tract center, while smoke exposure is measured as the annual count of days with $PM_{2.5}$ concentrations above 40 $\mu g/m^3$. The specification includes up to three annual lags of both wildfire and smoke exposure to capture delayed and persistent effects, allowing us to examine how environmental shocks influence household migration dynamics over time. We apply the same regression framework to the firm-level data to estimate the impact of wildfire and smoke exposure on firm performance. The dependent variables include firm employment, sales, and survival, with additional heterogeneity analyses by firm size and sector. This analysis provides complementary evidence on how environmental shocks affect local economic activity through both direct operational disruptions and indirect labor supply channels. Second, we estimate a residential sorting model with endogenous amenities.

Our empirical analysis shows that both wildfire and smoke exposures generate substantial and persistent demographic and economic responses. At the tract level, a one-standard-deviation increase in smoke exposure reduces household counts by 0.3-0.4% annually over the following three years, while wildfire exposure lowers them by 0.15-0.2%. The effects of smoke are especially persistent and concentrated among older households: tracts with higher smoke exposure experience lasting declines in households headed by individuals aged 50 and above, while the number of younger households gradually increases in subsequent years. These compositional shifts are accompanied by modest rises in homeownership rates and declines in home values, consistent with discounted property prices attracting new, younger entrants into affected housing markets.

Firms are also meaningfully affected. Smoke exposure leads to about a one-percent decline in the number of firms per standard deviation of smoke, with losses concentrated among small businesses (under $10 million in annual sales). Medium-sized firms are largely unaffected, while large firms expand slightly in smoke-affected areas, suggesting market reallocation and consolidation as smaller firms exit. Wildfire exposure itself has smaller and more localized impacts. These patterns highlight how wildfire and smoke jointly reshape local economic geography through both direct operational disruptions and indirect labor-supply and demand channels.

Our structural estimates reveal meaningful heterogeneity in households' willingness to pay to avoid wildfire smoke exposure. On average, households are willing to pay 3.2% of property value to avoid one standard deviation of mean seasonal smoke, lagged two years. Willingness to pay rises with age—reaching 4% among households over 65 and 2.4% among those under 35—consistent with greater sensitivity to health risks among older residents. These differences imply that wildfire smoke not only reduces aggregate welfare but also reshapes the demographic composition of communities, as more vulnerable or higher-income households are disproportionately likely to relocate from highly exposed areas. On the firm side, changes in demographic composition translate into shifts in the local economic structure: sectors catering to older or higher-income populations—such as health care, real estate, and retail—contract following persistent smoke exposure, while sectors serving younger populations or essential services, including construction and logistics, exhibit relative resilience or modest expansion. These patterns underscore the tight link between demographic sorting and sectoral specialization in local service provision, highlighting how environmental shocks can generate long-lasting adjustments in both household welfare and the spatial organization of economic activity. The model structure also enables a range of counterfactual exercises: for instance, simulating welfare and migration outcomes under alternative smoke scenarios (e.g., a 50% reduction in smoke exposure or a doubling of extreme smoke days), examining the general-equilibrium effects of targeted adaptation policies or sector-specific subsidies, and assessing how improvements in air quality or wildfire management would alter household sorting, firm dynamics, and welfare distribution across demographic groups.

Our results contribute to three strands of literature. First, we add to work on the economic and health consequences of wildfires Ang (2024); Heft-Neal et al. (2022); Knittel and Krebs (2024); Kochi et al. (2016); Moeltner et al. (2013); Wang et al. (2021); Wang (2024), extending it to migration, firm behavior, and welfare. Second, we connect to research on spatial sorting and firm–household interactions Almagro and Domínguez-Iino (2025); Diamond and Gaubert (2022); Ferreira and Wong (2020); George and Waldfogel (2003); Qian and Tan (2021), explicitly building on Almagro and Domínguez-Iino (2025) by embedding their endogenous-amenity mechanism in a context of environmental shocks. Finally, we contribute to the broader climate adaptation literature by showing how indirect effects—via migration and firm responses—can exceed the direct damages from wildfire itself.

The paper is structured as follows. Section 2 describes the data sources, including household-level migration and housing data, firm-level performance metrics, and high-resolution environmental data on wildfire smoke exposure. Section 3 outlines the empirical setting and identification strategy used to estimate reduced-form relationships. Section 4 presents the reduced-form evidence on the effects of wildfire and smoke exposure on households and firms. Section 5 presents the structural residential sorting model with endogenous amenities. This section formalizes how households respond to smoke exposure when choosing locations, and how their relocation decisions shape the local amenity landscape. Section 6 discusses the estimation and results of the structural model, including heterogeneity in household preferences, the endogenous supply of amenities, and the demand for housing. Finally, Section 7 concludes by summarizing the key findings, outlining the policy implications, and highlighting directions for future research.

## 2 Data and Exposure Measures

Our analysis combines multiple datasets to provide a comprehensive understanding of the impacts of wildfire smoke. For wildfire smoke exposure, we use $PM_{2.5}$ data developed by prior studies Childs et al. (2022), calculating the annual mean and median smoke levels for each census tract. To analyze household demographics and locations, we utilize consumer data from Data Axle, focusing on residents of California from 2013 to 2019. This dataset comprises approximately 100 million observations and includes demographic attributes such as the age of the household head, presence of children, marital status, income, and home value. Crucially, it allows us to track household relocations within the United States.

In addition to these primary datasets, we will incorporate two additional sources: (1) wildfire data from the California Department of Forestry and Fire Protection (CAL FIRE), which provides detailed information on wildfire incidents, and (2) property characteristics and transactions data, which will enhance our understanding of housing market dynamics and relocation patterns.

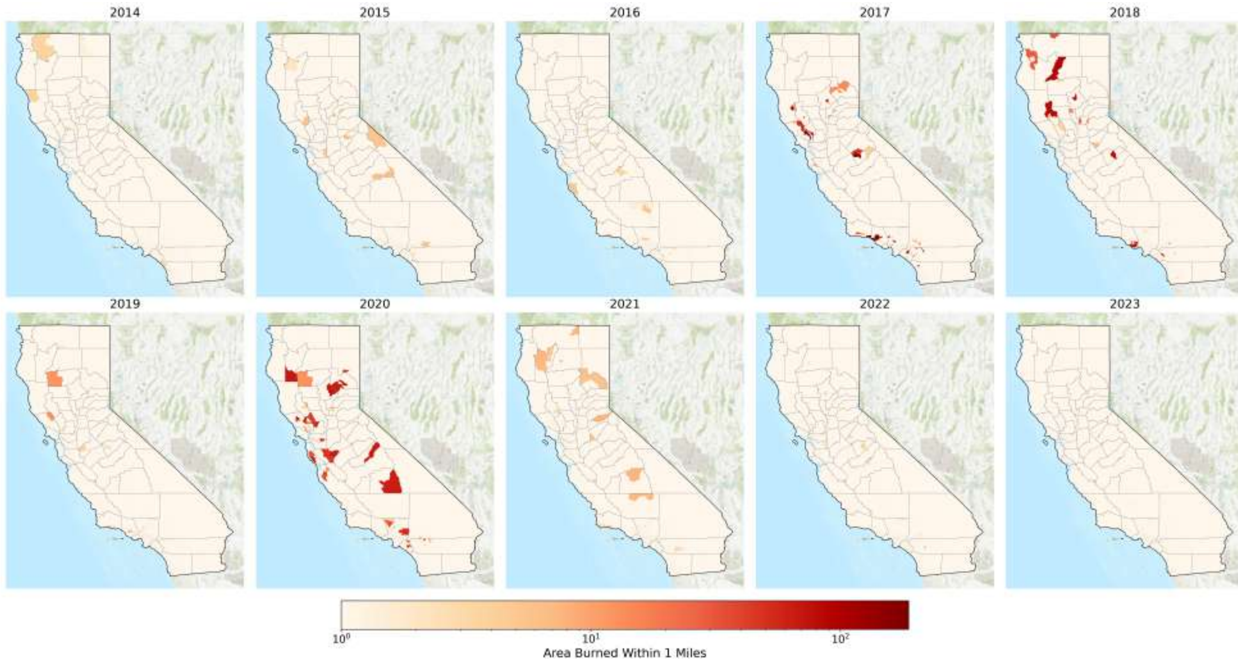
Currently, the data are aggregated at the census tract level to identify migration trends and analyze demographic patterns. Preliminary analyses answer the question of who moves, while future work will investigate where these households relocate. By incorporating individual-level analyses, we aim to provide a more nuanced understanding of migration and its broader implications.

Figure 1 compares wildfire proximity and smoke exposure at the census tract level in California from 2014 to 2023. Panel (a) shows the total area burned within one mile of each tract center, capturing the direct geographic impact of wildfires, while Panel (b) illustrates the number of days with $PM_{2.5}$ concentrations above 40 $\mu$g/m$^{\mathbf{3}}$, indicating the extent of smoke exposure. The figure highlights a key spatial distinction: wildfires themselves are highly localized, affecting a relatively small share of tracts in any given year, whereas smoke is far more dispersed, spreading across much larger areas and reaching tracts far from the burn zones. The progression of smoke intensity is represented by increasingly darker shades of red, indicating a higher number of days with elevated smoke levels. While relatively few tracts experienced frequent high-smoke days before 2017, conditions changed sharply in 2018 and became even more extreme in 2020 and 2021, when much of the state experienced prolonged periods of heavy smoke. In contrast, smoke exposure declined noticeably after 2021, reflecting reduced wildfire severity and more favorable atmospheric conditions. Appendix Figure A8 further illustrates wildfire smoke exposure using alternative thresholds—20, 30, 50, and 60 $\mu$g/m$^{\mathbf{3}}$—showing how the spatial extent of exposure varies with the definition of high-smoke days.

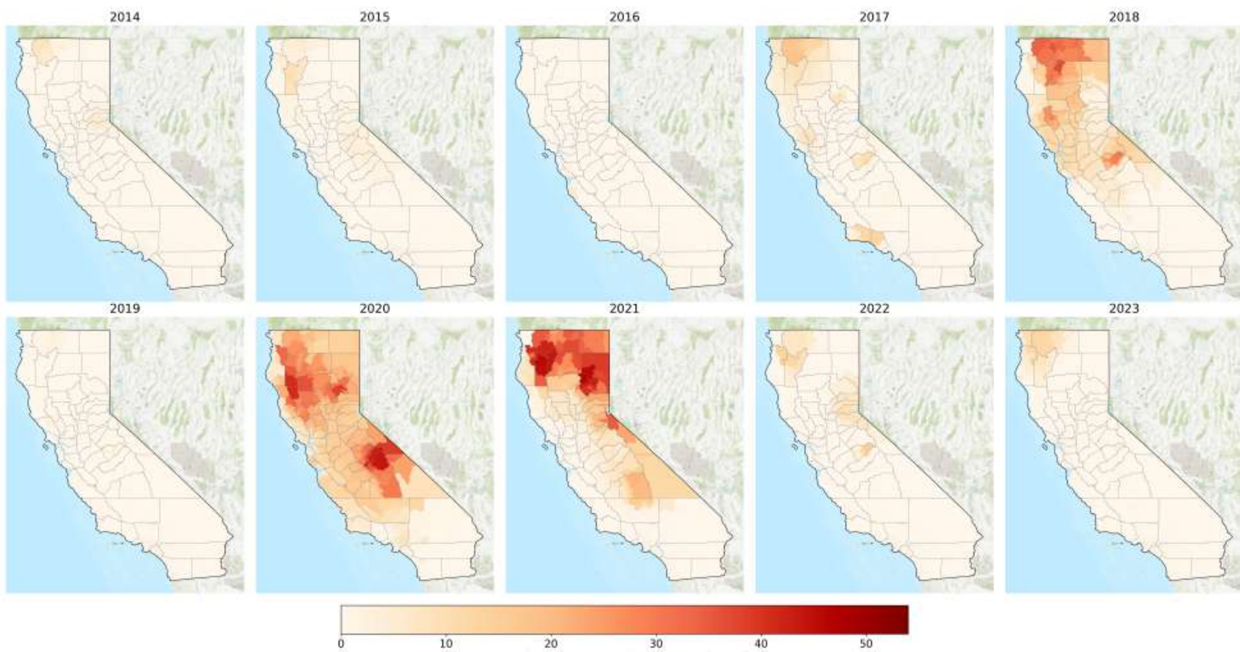
Figure A1 from Wang (2024) illustrates the increasing frequency of wildfires and mega-fires in California over the past three decades. Based on data from CAL FIRE, the graph highlights a notable rise in the number and severity of fires since 1990. Figure A2 from Knittel and Krebs (2024) presents the average annual wildfire smoke concentration ($PM_{2.5}$) categorized by quintiles of the overall distribution from 2006 to 2019. The figure shows how wildfire smoke exposure varies across regions, with higher quintiles experiencing significantly greater smoke concentrations.

Figure 2 presents county-level changes in the number of firms between 2014 and 2025. Panel (a) aggregates across all sectors, while Panel (b) focuses on the educatiion sector. Colors range from red (decline) to green (increase), with darker shades indicating larger percentage changes. Across all sectors (Panel a), the maps reveal relatively modest aggregate shifts over time—most counties exhibit relatively minor variations in firm counts, suggesting smaller changes at the county level. In contrast, the education sector (Panel b) displays greater spatial and temporal heterogeneity, with distinct pockets of growth and contraction across regions. Appendix figures A5 and A6 extend this comparison to other locally oriented service sectors—accommodation and restaurants, health, real estate, and retail; which exhibit similarly distinct geographic and temporal dynamics. Each sector has a different spatial and temporal trends.

Figure A3 presents the spatial distribution of household attributes at the tract level for 2017. The top two maps show the total household count per tract and the average age of residents, with urban areas tending to have a lower mean age. The bottom two maps illustrate the percentage of households with children and the percentage of owner-occupied households, highlighting variations in household composition



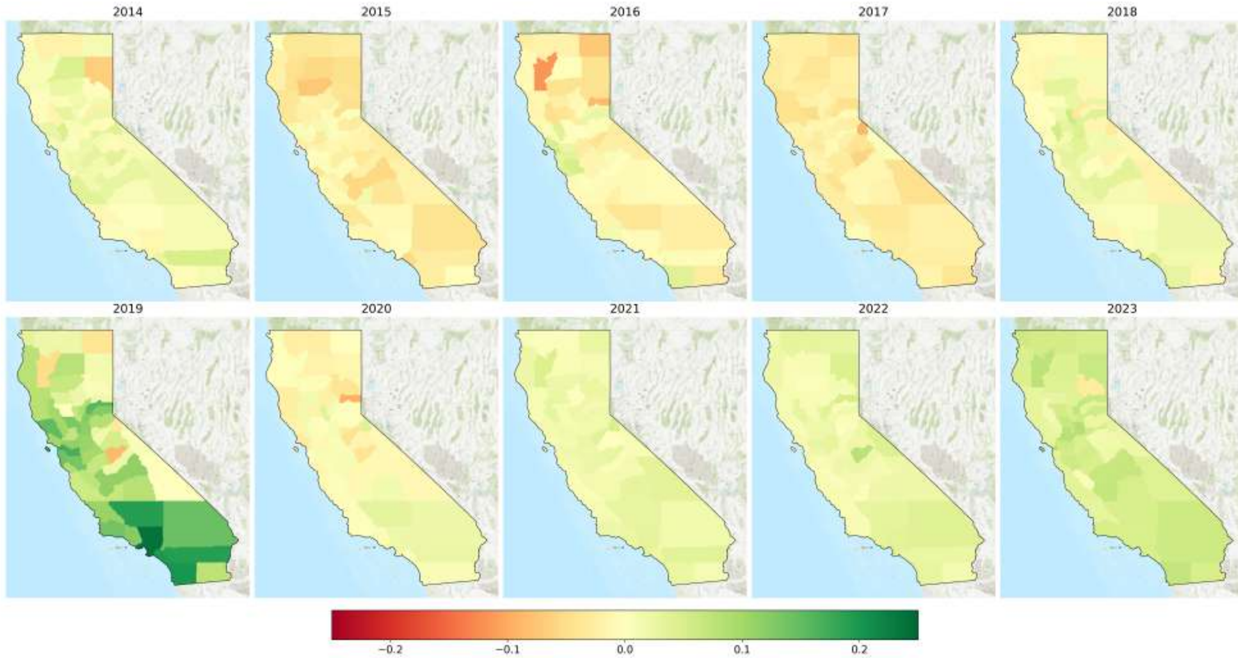

(a) Area burned within 1 mile of the census tract center, 2014–2023.



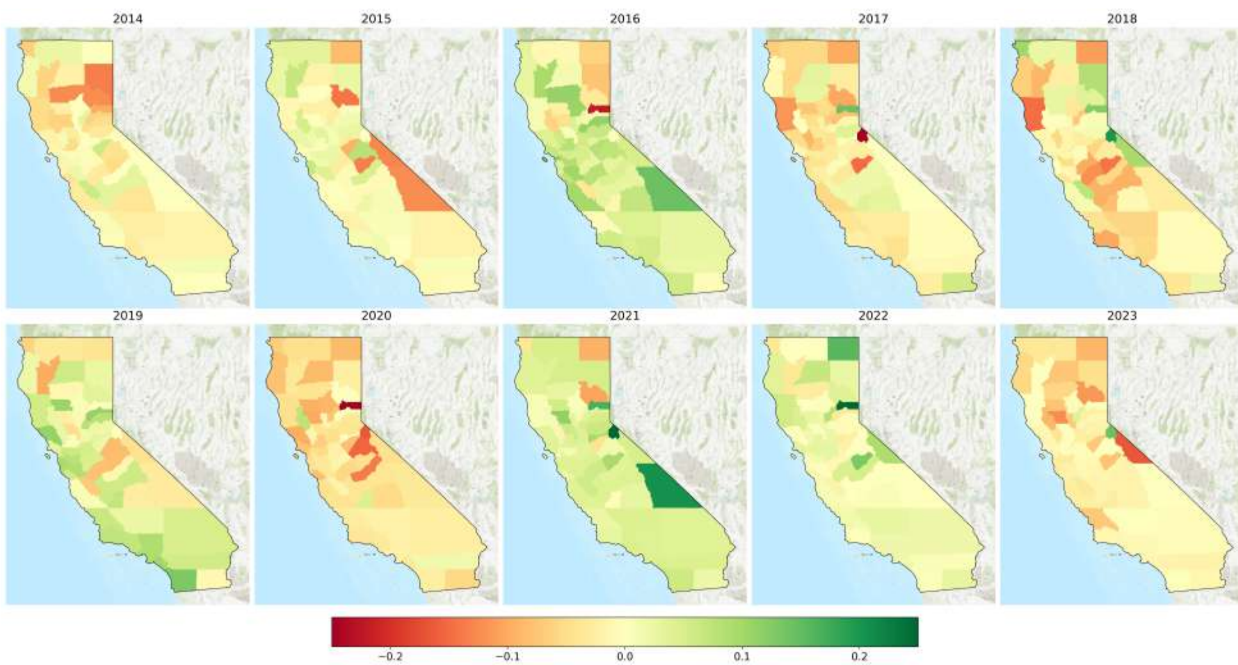

(b) Annual number of days with $PM_{2.5}$ concentrations above 40 $\mu$g/m$^3$ at the census tract level, 2014–2023.

Figure 1: (a) Area under wildfire within 1 mile of census tract centers; (b) annual number of days with $PM_{2.5}$ concentrations above 40 $\mu$g/m$^3$, both at the census tract level, 2014–2023.

*Note:* Panel (a) shows the area burned within one mile of each census tract center in California from 2014 to 2023. Panel (b) presents the number of days with smoke levels exceeding 40 $\mu$g/m$^3$ over the same period. While wildfires are spatially concentrated, smoke exposure is more widespread, affecting a much larger share of the state.




(a) Percentage change in the total number of firms across all sectors, 2014–2023.




(b) Percentage change in the number of firms in the education sector, 2014–2023.

Figure 2: County-level percentage change in firm counts for (a) all sectors and (b) the education sector, 2014–2023.

*Note:* Red indicates a decline and green an increase in the number of operating firms, with darker colors representing larger magnitudes of change. While overall county-level firm activity (Panel a) remains relatively stable, Panel (b) shows substantial sectoral and spatial variation, highlighting heterogeneity in firm dynamics across regions.

and homeownership across different regions. Figure A4 displays tract-level firm attributes for 2017. The top two maps show the total number of firms per tract and the average number of employees per firm, indicating firm size. Most tracts comprise smaller firms, with an average of fewer than 28 employees. The bottom two maps compare firm counts in the education and manufacturing sectors. While both sectors have similar median and mean firm counts, education-related firms are more evenly distributed, whereas manufacturing firms are more concentrated, with distinct clusters appearing in certain regions.

The reliability of consumer data has driven its increasing use in recent research. For instance, Christensen and Timmins (2023) employed Data Axle (formerly InfoUSA) consumer data, which offers detailed insights into household demographics and migration patterns. Similarly, Infutor data, another prominent consumer dataset, has been extensively utilized in studies such as Diamond et al. (2019), Diamond et al. (2020), Elliott and Wang (2023), and Wang (2024). A similar level of reliability is likely to hold for Data Axle firm data as well. Figure A7 from Cao et al. (2024) evaluates the reliability of Data Axle firm data by comparing county-level store counts for NAICS code 452 with corresponding store counts from the U.S. Census Bureau's County Business Patterns (CBP) data in 2019. The results indicate a high degree of consistency between Data Axle and CBP, reinforcing the credibility of Data Axle as a reliable source for firm-level analysis.

# 3 Empirical Setting and Identification

We examine the effects of wildfire exposure and smoke exposure on household and firm outcomes using a panel specification that leverages spatial and temporal variation in these two related but distinct environmental hazards over the 2011-2023 period. Wildfire exposure is measured as the total area burned within one mile of each census tract center, while smoke exposure is defined as the annual number of days with $PM_{2.5}$ concentrations exceeding 40 $\mu g/m^3$. Both measures are included jointly in the same model, allowing us to distinguish the localized effects of direct wildfire exposure from the broader impacts of smoke that can extend far beyond the immediate burn zones. Identification comes from spatial and temporal variation in these measures across tracts and years. As illustrated in Figure 1, wildfire exposure is spatially concentrated, whereas smoke exposure is more dispersed, reaching tracts with no nearby wildfire activity. The baseline specification is presented in Equation 1.

$$Y_{it} = \beta_0 + \sum_{k=1}^{3} \left( \beta_k^W \text{WildfireExposure}_{i,t-k} + \beta_k^S \text{SmokeExposure}_{i,t-k} \right) + \gamma_i + \delta_t + \epsilon_{it} \tag{1}$$

In Equation 1, $Y_{it}$ denotes the outcome for census tract $i$ in year $t$; $\text{WildfireExposure}_{i,t-k}$ is the total area burned within one mile of tract $i$, lagged $k$ years; and $\text{SmokeExposure}_{i,t-k}$ is the number of days with

$PM_{2.5}$ concentrations above 40 $\mu$g/m$^3$, also lagged $k$ years. The model includes tract fixed effects ($\gamma_i$) and year fixed effects ($\delta_t$) to account for time-invariant local characteristics and statewide shocks. This lag-only structure captures the delayed and persistent effects of wildfire and smoke exposure on both household and firm outcomes between 2011 and 2023, recognizing that their economic and demographic impacts may unfold gradually over multiple years.

Here, the coefficients $\beta_k^W$ and $\beta_k^S$ capture the lagged effects of wildfire and smoke exposure, respectively, on the outcomes of interest. On the household side, the dependent variables include the count of households (overall and disaggregated by demographic attributes such as age and marital status), as well as property value, wealth, and income. On the firm side, the dependent variables include employment, sales, and firms' operating status, further disaggregated by firm size and sector. This approach allows us to estimate the dynamic effects of both wildfire and smoke exposure on local economic and demographic outcomes, providing a comprehensive understanding of their short- and medium-term impacts.

# 4 Reduced-Form Evidence

## 4.1 Household Migration

Table 1 reports estimates from Equation 1, which examines the causal effects of wildfire and smoke exposure on household counts at the census tract level. The dependent variable is the log of the total number of households, and both wildfire and smoke exposure variables are standardized to have a mean of zero and a standard deviation of one. Specification (1) includes only the first lag of each exposure variable, while Specifications (2) and (3) sequentially add second and third lags to capture persistence in the effects over time.

The results show that both wildfire and smoke exposure cause statistically significant declines in household counts. In Specification (1), a one standard deviation increase in wildfire exposure causes household counts to decline by approximately 0.132%, while a comparable increase in smoke exposure causes a 0.153% decline in the first year. As additional lags are included, the magnitude and sign of the coefficients remain remarkably stable, suggesting that these effects are persistent rather than transitory. Wildfire exposure produces durable population losses, with significant coefficients across all three lags, consistent with longer-term displacement and reduced in-migration following nearby fire activity. Smoke exposure also leads to notable short-run declines, though the effects attenuate with time, indicating that the influence of smoke is more immediate but less persistent. Taken together, the estimates indicate that both wildfire and smoke exposure cause meaningful and lasting disruptions to local population dynamics.

Table 1: Effects of Wildfire and Smoke Exposure on Household Counts

| | (1) | (2) | (3) |
|---|---|---|---|
| Wildfire lag 1 | -0.00070* | -0.00085** | -0.00132*** |
| | (0.0004) | (0.0004) | (0.0003) |
| Wildfire lag 2 | | -0.00106*** | -0.00149*** |
| | | (0.0004) | (0.0003) |
| Wildfire lag 3 | | | -0.00163*** |
| | | | (0.0004) |
| Smoke lag 1 | -0.00288*** | -0.00275*** | -0.00153*** |
| | (0.0005) | (0.0005) | (0.0004) |
| Smoke lag 2 | | -0.00454*** | -0.00324*** |
| | | (0.0005) | (0.0005) |
| Smoke lag 3 | | | -0.00153*** |
| | | | (0.0005) |
| Observations | 68,134 | 68,133 | 61,939 |
| Adjusted $R^2$ | 0.96 | 0.96 | 0.97 |

*Notes:* Estimates correspond to Equation 1. The dependent variable is the log count of households at the census tract level. All models include tract and year fixed effects. Standard errors, clustered at the tract level, are reported in parentheses. Wildfire and smoke exposure variables are normalized to have a mean of zero and a unit standard deviation. Coefficients reflect the percent change in household counts caused by a one standard deviation increase in exposure. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Building on the preferred specification (Specification 3 in Table 1), Table 2 examines heterogeneity in the effects of wildfire and smoke exposure across household age groups (head of the household). The dependent variable is the count of households in each age category at the census tract-year level. Column (1) reports the baseline estimates for all households, while Columns (2)-(5) disaggregate the sample by age group of the household head.

Several patterns emerge. First, wildfire exposure causes a decline in household counts among tracts with residents aged 35 and older, with the largest effects concentrated among those aged 50-65. A one standard deviation increase in wildfire exposure leads to an estimated 0.2-0.3% reduction in household counts for these age groups, consistent with longer-term relocation or reduced inflows following nearby fire activity. By contrast, smoke exposure has particularly strong effects on older households. Households headed by individuals aged 50 and above experience pronounced declines in response to smoke, with effects exceeding 0.5% in several lags, indicating that prolonged smoke events have substantial impacts on older populations. Interestingly, the households (under 35 and 35 to 50) display small positive coefficients for smoke exposure, suggesting short-run inflows or temporary migration toward affected areas—possibly reflecting differences in mobility costs or economic opportunities following fire events. Overall, these results reveal clear heterogeneity in population responses, with wildfire and smoke exposure causing significant and persistent declines in older household populations.

Next, we explore how wildfire and smoke exposure affect the demographic and housing attributes of households. Table 3 reports estimates from Equation 1 where the dependent variables capture tract-level averages of household characteristics: mean age of household head, share of households with children, share of owner-occupied households, and mean home vaAs before, wildfire and smoke exposure variables are standardized to have a mean of zero and a unit standard deviation, and all models include tract and year fixed effects.

The results show that smoke exposure causes consistently larger and more negative effects than wildfire exposure. A one standard deviation increase in smoke exposure reduces the mean age of household heads by roughly 0.03–0.06 years, consistent with the earlier finding in Table 2 that tracts lose relatively older households after exposure events. The share of households with children also declines, suggesting that families tend to relocate away from more smoke-affected areas. In contrast, the share of owner-occupied households increases modestly following smoke exposure, indicating that younger or middle-aged households who move into smoky tracts may be more likely to purchase rather than rent homes—possibly due to lower property prices or reduced competition in the housing market. Finally, home values decline significantly with smoke exposure, with effects ranging between 0.2–0.3%, consistent with capitalization of environmental risk into property prices. Overall, these results reinforce the demographic sorting patterns observed earlier: wildfire and smoke exposure not only reduce population counts but also reshape the composition and housing

Table 2: Heterogeneous Effects of Wildfire and Smoke Exposure on Household Counts by Age Group

| | All | <35 | 35–50 | 50–65 | >65 |
|---|---|---|---|---|---|
| Wildfire lag 1 | -0.00132*** | -0.00035 | -0.00111** | -0.00170*** | -0.00138*** |
| | (0.0003) | (0.0007) | (0.0005) | (0.0003) | (0.0004) |
| Wildfire lag 2 | -0.00149*** | 0.00002 | -0.00084* | -0.00249*** | -0.00172*** |
| | (0.0003) | (0.0007) | (0.0005) | (0.0003) | (0.0004) |
| Wildfire lag 3 | -0.00163*** | 0.00066 | -0.00104** | -0.00329*** | -0.00205*** |
| | (0.0004) | (0.0007) | (0.0005) | (0.0004) | (0.0005) |
| Smoke lag 1 | -0.00153*** | 0.00245*** | 0.00327*** | -0.00569*** | -0.00663*** |
| | (0.0004) | (0.0009) | (0.0007) | (0.0004) | (0.0006) |
| Smoke lag 2 | -0.00324*** | -0.00186** | 0.00455*** | -0.00862*** | -0.00916*** |
| | (0.0005) | (0.0009) | (0.0007) | (0.0005) | (0.0006) |
| Smoke lag 3 | -0.00153*** | 0.00025 | 0.00401*** | -0.00540*** | -0.00543*** |
| | (0.0005) | (0.0009) | (0.0007) | (0.0005) | (0.0006) |
| Observations | 61,939 | 61,939 | 61,939 | 61,939 | 61,939 |
| Adjusted $R^2$ | 0.97 | 0.93 | 0.95 | 0.97 | 0.97 |

*Notes:* Estimates correspond to the preferred specification (Specification 3 in Table 1) from Equation 1. The dependent variable is the count of households in each age group at the census tract-year level by different age groups. All models include tract and year fixed effects. Standard errors, clustered at the Wildfire and smoke exposure variables, are normalized to have a mean of zero and a unit standard deviation. Coefficients reflect the percent change in household counts caused by a one standard deviation increase in exposure. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

structure of affected communities.

## 4.2 Effects on Firms

We next examine how wildfire and smoke exposure affect local economic activity by estimating Equation 1 using the *log of the number of firms* in each census tract-year as the dependent variable. As before, wildfire and smoke exposure variables are standardized to have a mean of zero and a standard deviation of one, and all models include tract and year fixed effects. Table 4 reports results from three specifications that progressively add lags to capture the persistence of the effects over time.

The results show that smoke exposure causes substantial and persistent declines in firm activity, while wildfire exposure has limited direct effects. In Specification (1), a one standard deviation increase in smoke exposure causes a 1.15% reduction in the number of firms, and the effect remains negative and statistically significant as additional lags are introduced. By contrast, wildfire exposure coefficients are small and statistically insignificant in most cases, with only the third lag showing a marginal effect. This pattern suggests that while wildfires have localized impacts on households and property, it is the broader and more diffuse smoke exposure that disrupts business operations and deters firm presence. The persistence of negative smoke coefficients across multiple lags indicates that smoke exposure not only affects short-term business

Table 3: Effects of Wildfire and Smoke Exposure on Household Attributes

| | Mean Age | % HH with Child | % HH Owners | Home Value |
|---|---|---|---|---|
| Wildfire lag 1 | -0.00103 | 0.00008 | -0.00024 | -0.00008 |
| | (0.0030) | (0.0001) | (0.0002) | (0.0002) |
| Wildfire lag 2 | -0.00280 | 0.00006 | -0.00027* | 0.00001 |
| | (0.0031) | (0.0001) | (0.0002) | (0.0002) |
| Wildfire lag 3 | -0.00455 | 0.00001 | -0.00038** | -0.00022 |
| | (0.0032) | (0.0001) | (0.0002) | (0.0002) |
| Smoke lag 1 | -0.05553*** | -0.00048*** | 0.00126*** | -0.00108 |
| | (0.0040) | (0.0001) | (0.0002) | (0.0007) |
| Smoke lag 2 | -0.04898*** | -0.00051*** | 0.00251*** | -0.00231*** |
| | (0.0041) | (0.0001) | (0.0002) | (0.0007) |
| Smoke lag 3 | -0.02881*** | -0.00055*** | 0.00231*** | -0.00192** |
| | (0.0043) | (0.0001) | (0.0002) | (0.0008) |
| Observations | 61,939 | 61,939 | 61,939 | 61,909 |
| Adjusted $R^2$ | 0.96 | 0.95 | 0.91 | 0.99 |

*Notes:* The dependent variables are tract-level household attributes: mean age of household head, share of households with children, share of owner-occupied households, and mean home value. All models include tract and year fixed effects. Standard errors, clustered at the tract level, are reported in parentheses. Wildfire and smoke exposure variables are normalized to have mean zero and unit standard deviation. Coefficients represent the change in the dependent variable caused by a one standard deviation increase in exposure. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

activity but may also lead to sustained economic adjustments as firms relocate or delay investment in affected regions.

Table 4: Effects of Wildfire and Smoke Exposure on Firm Counts

| | (1) | (2) | (3) |
|---|---|---|---|
| Wildfire lag 1 | 0.00003 | -0.00012 | -0.00030 |
| | (0.0005) | (0.0005) | (0.0005) |
| Wildfire lag 2 | | -0.00040 | -0.00024 |
| | | (0.0005) | (0.0005) |
| Wildfire lag 3 | | | -0.00084* |
| | | | (0.0005) |
| Smoke lag 1 | -0.01153*** | -0.01082*** | -0.00916*** |
| | (0.0006) | (0.0006) | (0.0005) |
| Smoke lag 2 | | -0.01649*** | -0.01516*** |
| | | (0.0006) | (0.0006) |
| Smoke lag 3 | | | -0.01361*** |
| | | | (0.0006) |
| Observations | 53,711 | 53,705 | 48,818 |
| Adjusted $R^2$ | 0.98 | 0.98 | 0.98 |

*Notes:* The dependent variable is the log count of firms in each census tract and year. All models include tract and year fixed effects. Standard errors, clustered at the tract level, are reported in parentheses. Wildfire and smoke exposure variables are normalized. Coefficients represent the percent change in firm counts caused by a one standard deviation increase in exposure. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

We further investigate heterogeneity in firm responses to wildfire and smoke exposure by firm size, measured both by annual revenue and by number of employees. Firm size by revenue is grouped into four categories: less than $1 million, $1-10 million, $10-100 million, and more than $100 million in annual sales. We estimate Equation 1 using the *log of the number of firms* in each size category as the dependent variable.

The results in Table 5 reveal strong heterogeneity by firm size. Smoke exposure causes large declines in the number of small firms (less than $10 million in annual revenue), with the effects exceeding 1% for every one standard deviation increase in exposure. These results indicate that small firms are particularly vulnerable to smoke events, likely due to liquidity constraints or reduced demand during disruption periods. Medium-sized firms (10–100 million) show no systematic response, suggesting relative resilience or offsetting mechanisms. In contrast, large firms (more than $100 million) exhibit positive and statistically significant coefficients, implying that they increase their presence in more smoke-affected areas, possibly due to market consolidation, expansion opportunities, or reduced competition from smaller firms exiting the local market. Wildfire exposure itself shows minimal effects across all firm sizes, consistent with earlier results indicating that direct fire damage is spatially limited. Similar patterns emerge when firm size is measured by the number of employees. These results suggest that wildfire smoke exposure reshapes the local industrial composition by driving out smaller businesses while larger firms consolidate their market position.

Table 5: Heterogeneous Effects of Wildfire and Smoke Exposure by Firm Size (Annual Revenue)

| | <1M | 1-10M | 10-100M | >100M |
|---|---|---|---|---|
| Wildfire lag 1 | -0.00057 | -0.00086 | 0.00152 | 0.00128 |
| | (0.0005) | (0.0007) | (0.0016) | (0.0034) |
| Wildfire lag 2 | -0.00059 | -0.00132* | 0.00036 | -0.00373 |
| | (0.0005) | (0.0007) | (0.0017) | (0.0036) |
| Wildfire lag 3 | -0.00035 | -0.00239*** | -0.00153 | -0.00304 |
| | (0.0005) | (0.0007) | (0.0018) | (0.0034) |
| Smoke lag 1 | -0.00348*** | -0.01120*** | -0.00239 | 0.00696* |
| | (0.0006) | (0.0008) | (0.0019) | (0.0037) |
| Smoke lag 2 | -0.00860*** | -0.01312*** | -0.00180 | 0.01026*** |
| | (0.0006) | (0.0008) | (0.0019) | (0.0039) |
| Smoke lag 3 | -0.00998*** | -0.00874*** | -0.00226 | 0.00934** |
| | (0.0006) | (0.0009) | (0.0021) | (0.0041) |
| Observations | 48,818 | 48,818 | 44,833 | 12,848 |
| Adjusted $R^2$ | 0.97 | 0.97 | 0.91 | 0.80 |

*Notes:* The dependent variable is the log count of firms in each size category based on annual revenue (in millions). All models include tract and year fixed effects. Standard errors, clustered at the tract level, are reported in parentheses. Coefficients represent the percent change in firm counts caused by a one standard deviation increase in exposure. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

As a robustness check, we redefine firm size by employment rather than annual revenue. Table B3 in Appendix B reports results, where firms are grouped into four categories based on the number of employees. The pattern of results remains consistent with those in Table 5: smaller firms experience the largest negative effects of smoke exposure, while larger firms show positive or insignificant responses, suggesting consolidation among surviving firms following exposure events.

Table 6 presents the effects of wildfire and smoke exposure on firm performance, measured in logs of total and average outcomes. The results show that smoke exposure causes a persistent decline in both total sales and total employment, with coefficients ranging from 0.6 to 1 percent across lags. These reductions suggest that smoke events significantly disrupt local business activity. At the same time, mean employment per firm increases, indicating that the contraction in total activity is driven primarily by the exit of smaller firms rather than widespread downsizing among surviving firms. This pattern is consistent with earlier evidence of firm-size heterogeneity, where smoke exposure leads to market consolidation as small firms exit and larger firms expand their presence.

Table 6: Effects of Wildfire and Smoke Exposure on Firm Performance

| | Log Sum Sale | Log Sum Emp | Log Mean Sale | Log Mean Emp |
|---|---|---|---|---|
| Wildfire lag 1 | 0.00080 | 0.00026 | 0.00138 | 0.00104 |
| | (0.0012) | (0.0007) | (0.0012) | (0.0007) |
| Wildfire lag 2 | -0.00095 | -0.00091 | -0.00022 | -0.00019 |
| | (0.0013) | (0.0008) | (0.0012) | (0.0007) |
| Wildfire lag 3 | 0.00009 | -0.00008 | 0.00083 | 0.00101 |
| | (0.0013) | (0.0008) | (0.0013) | (0.0008) |
| Smoke lag 1 | -0.00653*** | -0.00089 | -0.00175 | 0.00363*** |
| | (0.0015) | (0.0009) | (0.0014) | (0.0008) |
| Smoke lag 2 | -0.01003*** | -0.00366*** | -0.00117 | 0.00608*** |
| | (0.0015) | (0.0009) | (0.0014) | (0.0009) |
| Smoke lag 3 | -0.00757*** | -0.00543*** | 0.00140 | 0.00470*** |
| | (0.0016) | (0.0010) | (0.0015) | (0.0009) |
| Observations | 48,818 | 48,818 | 48,818 | 48,818 |
| Adjusted $R^2$ | 0.94 | 0.97 | 0.87 | 0.91 |

*Notes:* The dependent variables are the logarithms of tract-level firm outcomes: total sales (Log Sum Sale), total employment (Log Sum Emp), average firm sales (Log Mean Sale), and average firm employment (Log Mean Emp). All regressions include tract and year fixed effects. Standard errors, clustered at the tract level, are reported in parentheses. Wildfire and smoke exposure variables are normalized to have a mean of zero and a unit standard deviation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

## 4.3 Robustness

To test the robustness of the baseline results reported in Table 1, we use Specification (3), which measures the impact of wildfire and smoke exposure on the *log of the count of households* at the census tract level. We re-estimate this specification using alternative definitions of wildfire and smoke exposure while holding the model structure constant.

Panel A of Table B1 in Appendix B fixes the smoke exposure measure to the annual number of days with $PM_{2.5}$ concentrations above 40 $\mu g/m^3$ and varies the spatial radius used to define wildfire exposure—from total burned area statewide to burned area within 1, 5, and 10 miles of each tract centroid. The estimated effects remain highly consistent with the baseline results: wildfire exposure continues to have negative and persistent impacts on household counts, with the strongest effects observed within a one-mile radius.

Panel B holds the wildfire exposure measure fixed to the area burned within one mile and instead varies the definition of smoke exposure. We compare the mean seasonal $PM_{2.5}$ concentration and the number of high-smoke days above thresholds of 30, 40, and 50 $\mu g/m^3$. The coefficients are remarkably stable across these alternative smoke measures, and the persistence of the negative effects confirms that our main results are not sensitive to the precise construction of either exposure variable. Overall, these robustness checks reinforce the findings from Table 1 that both wildfire and smoke exposure cause statistically significant and persistent declines in household counts.

Similar to the robustness analysis for household counts, Table B2 in Appendix B reports robustness checks for firm outcomes using Specification (3) of Table 4. The dependent variable is the *log of the count of firms* at the census tract level.

Panel A fixes the smoke exposure measure to annual days with $PM_{2.5}$ above 40 $\mu g/m^3$ and varies wildfire exposure by spatial radius.Panel B fixes wildfire exposure to the area burned within one mile and varies alternative smoke measures. Results are stable across definitions—smoke exposure consistently shows large and persistent negative effects on firm counts, while wildfire effects remain small.

# 5 Residential Sorting Model with Endogenous Amenities

Wildfires and their smoke significantly impact firms' performance, both directly and indirectly. Direct impacts include infrastructure damage, utility interruptions, hindered operations, and higher insurance premiums. Indirectly, firms face revenue losses, reduced employee availability, and lower productivity due to the effects of smoke and wildfires on households. However, much of the existing literature focuses on the "wildfire" itself—the immediate destruction—rather than the "smoke," which represents the lingering, pervasive, and often overlooked consequences. This study shifts the focus to the smoke, examining how its indirect effects ripple through households and firms, shaping long-term economic and social outcomes.

We employ a residential sorting model to address several key questions. Non-marginal changes in amenities, such as wildfire smoke, require a structural approach to understand their impacts. The model allows us to analyze how externalities, like smoke, affect housing markets, consumer choices, and firm performance. It also helps us uncover the mechanisms driving household and firm behavior. Furthermore, the model enables counterfactual analysis with sorting and price adjustments, providing insights into welfare implications.

This section models how households choose locations based on amenities that are themselves endogenously determined by the demographic composition of the area. Following Almagro and Domínguez-Iino (2025), we allow amenities to respond to the local population structure, thereby linking household sorting with equilibrium amenity supply.

Households derive utility from property attributes, rents, idiosyncratic preferences, a vector of local amenities, and smoke levels. Unlike standard models that treat amenities as exogenous, here the amenity bundle in each location depends on the number and type of households that choose to live there. This captures a core mechanism through which local demographic changes, such as those triggered by climate-induced migration, transform the spatial distribution of public and private goods.

The endogenous nature of amenities creates feedback loops. For example, when high-income or older households migrate to a location in response to a shock (e.g., wildfires), they increase demand for specific amenities, such as health services. Firms respond to this demand by entering sectors that cater to these preferences, further strengthening the attraction of the location to similar households. This feedback mechanism amplifies spatial inequality in amenity provision and reshapes the long-run geographic distribution of populations.

## 5.1 Notation

We consider a spatial framework consisting of $J$ interior locations (e.g., census tracts). The time is indexed by $t$. Households are categorized into $K$ types. These include $K$ distinct local household types (such as renters, low-income owners, and high-income owners). Each type differs in its preferences over consumption amenities, income levels, and housing demand.

The population composition of location $j$ at time $t$ is denoted by the vector.

$$M_{jt} = \left[M_{jt}^1, \ldots, M_{jt}^K, M_{jt}^T\right]', \tag{2}$$

where $M_{jt}^k$ represents the number of households of type $k$ residing at location $j$ at time $t$.

The amenities in each location arise from the presence of firms operating in different consumption sectors $S$. Each sector is composed of differentiated varieties supplied by individual firms. For example, in the restaurant sector, each establishment offers a unique variety of options. In this context, we use the terms 'firm' and 'variety' interchangeably. Let $N_{sjt}$ denote the number of firms operating in sector $s$ at location $j$ at time $t$. Then, the vector of amenities available at the location $j$ at time $t$ is given by

$$a_{jt} = \left[N_{1jt}, \ldots, N_{Sjt}\right]'. \tag{3}$$

## 5.2 Endogenous Amenities

### 5.2.1 Demand for Amenities

Following Almagro and Domínguez-Iino (2025), households have Cobb–Douglas preferences over housing $H$ and a composite of consumption amenities $C$, with $\phi_k$ denoting the expenditure share on $C$ for a household of type $k$. Let $w_k^t$ denote the income of type $k$ households at time $t$, so that total expenditures on housing and on the amenity composite are $(1 - \phi_k)w_k^t$ and $\phi_k w_k^t$, respectively.

Conditional on choosing location $j$, a type-$k$ household allocates its after-rent income $\phi_k w_k^t$ across locally available amenity sectors and individual varieties. We assume households have Cobb–Douglas preferences across sectors and CES preferences within each sector. Hence, the quantity demanded by a type-$k$ household for variety $i$ in sector $s$, location $j$, and time $t$ is

$$q_{isjt}^k = \alpha_s^k \, \phi_k \, w_k^t \, \frac{1}{p_{isjt}} \left( \frac{p_{isjt}}{P_{sjt}} \right)^{1-\sigma_s}, \qquad P_{sjt} \equiv \left( \sum_{i=1}^{N_{sjt}} p_{isjt}^{1-\sigma_s} \right)^{\frac{1}{1-\sigma_s}}, \tag{4}$$

where $\alpha_s^k$ is the sectoral budget share, $\sigma_s > 1$ is the elasticity of substitution across varieties, $p_{isjt}$ is the price of variety $i$, and $P_{sjt}$ is the sector-level price index.

Total demand for a firm $i$ in sector $s$ is obtained by summing over all household types and weighting by their local population size $M_{jt}^k$:

$$q_{isjt} = \sum_k q_{isjt}^k \, M_{jt}^k. \tag{5}$$

This formulation captures how local demographic composition directly shapes the demand environment faced by firms in each sector-location. A tract populated by older or wealthier households, for instance, will have higher demand for amenities such as health or real estate services, while younger or lower-income populations may demand more entertainment and retail services.

#### 5.2.2 Supply of Amenities and Market Clearing

Firms operate under monopolistic competition and free entry in each sector-location market. Every firm faces the same marginal cost $c_{sjt}$ and a fixed operating cost $F_{sjt}$ that may vary across locations and over time.

Given these assumptions, all firms in the same sector-location choose identical prices and quantities. The optimal pricing rule under CES demand is

$$p_{isjt} = c_{sjt} \frac{\sigma_s}{\sigma_s - 1} \quad \forall i \in (s, j, t) \quad \Rightarrow \quad p_{isjt} = p_{sjt}, \, q_{isjt} = q_{sjt}. \tag{6}$$

Free entry drives profits to zero, implying that firms enter until:

$$(p_{sjt} - c_{sjt}) q_{sjt} = F_{sjt}(N_{jt}), \tag{7}$$

where $N_{jt} = \sum_s N_{sjt}$ denotes the total number of firms in location $j$ at time $t$. The fixed cost $F_{sjt}$ may increase with the total number of firms in the location to capture congestion effects such as competition for commercial space or higher local wages.

Combining equations (5)–(7) yields the equilibrium number of firms in each sector-location:

$$N_{sjt} = \frac{1}{\sigma_s F_{sjt}} \sum_k \alpha_s^k \, \phi_k \, w_k^t \, M_{jt}^k. \tag{8}$$

Equation (8) provides the key link between local demographics and the supply of amenities: sectors with stronger demand from particular demographic groups will see greater firm entry and higher local amenity supply.

#### 5.2.3 Equilibrium Amenities

Defining the vector of amenities in location $j$ at time $t$ as $a_{jt} = [N_{1jt}, N_{2jt}, \ldots, N_{Sjt}]$, we can express the equilibrium mapping between population composition and amenities as:

$$a_{jt} = \mathcal{A}(M_{jt}), \tag{9}$$

where $\mathcal{A}(\cdot)$ is an equilibrium correspondence that maps the local population composition $M_{jt}$ to the vector of sectoral amenities $a_{jt}$ by imposing market clearing in the amenity market.

Equation (9) illustrates the key mechanism in the model: changes in demographic composition—such as an inflow of older households or higher-income residents—alter the relative demand across sectors, prompting firms to adjust their entry decisions and changing the mix of local amenities. In equilibrium, amenities respond endogenously to residential sorting, generating a feedback loop between household composition and local economic structure.

#### 5.2.4 Interpretation

Equations (8)–(9) formalize the core of the endogenous amenities mechanism. A location's demographic composition determines its amenity supply through sector-specific demand and firm entry, while these amenities in turn influence future residential choices. High-income or older households, for example, generate stronger demand for health services, while younger households increase demand for accommodation and leisure sectors.

This feedback loop is central to our equilibrium interpretation: demographic sorting and firm entry co-evolve, producing heterogeneous local service structures across space. These equilibrium amenities not only reflect residents' preferences but also amplify spatial differences, shaping both neighborhood character and welfare outcomes across household types.

### 5.3 Housing Demand

We develop a static residential sorting model based on Bayer et al. (2007) to analyze household location decisions. Each household, denoted by $i$ of type $k$, derives utility $U_{ht}^i$ from choosing housing type $h$ (in location j) in time period $t$. The utility function is specified as:

$$\max_{ht} U_{ht}^i = \alpha_X^k X_{ht} + \alpha_A^k A_{ht} + \alpha_S^k S_{ht} + \alpha_p^k p_{ht} + \xi_{ht} + \epsilon_{ht}^i \tag{10}$$

The utility depends on several observed and unobserved components. The observed components include $X_{ht}$, which represents the characteristics of the property and neighborhood; $p_{ht}$, the price of property $h$ at time $t$; $A_{ht}$, amenities provided by firms in the area; and $S_{ht}$, the level of smoke exposure at property $h$ during or after the event. The unobserved components include $\xi_{ht}$, which captures unobserved utility from the property type and neighborhood at time $t$, and $\epsilon_{ht}^i$, an idiosyncratic taste shock for household $i$ at time $t$.

### 5.4 Heterogeneity in Preferences

Household preferences are allowed to vary by their type k.

The utility function can then be decomposed into mean utility ($\delta_{ht}$) and deviations from the mean utility ($\lambda_{ht}^i$):

$$U_{ht}^i = \underbrace{\delta_{ht}}_{\text{mean utility}} + \underbrace{\lambda_{ht}^i + \epsilon_{ht}^i}_{\text{deviation from mean utility}} \tag{11}$$

The idiosyncratic preference shocks, $\epsilon_{ht}^i$, are assumed to be independently and identically distributed (iid) and drawn from a Type 1 Extreme Value (T1EV) distribution.

## 6 Estimation and Model Results

### 6.1 Household heterogeneity

To operationalize the household side of the model, we classify households into four types based on the age of the household head: (1) under 35, (2) 35–50, (3) 50–65, and (4) above 65. Younger households tend to be more mobile, have lower wealth, and are more likely to rent, while older households exhibit higher ownership rates and greater accumulated assets. These age-based distinctions shape both residential location preferences and the demand for local amenities, which in turn influence the equilibrium composition of firms across counties.

Amenities are provided by five local service sectors: Accommodation and Restaurants, Education, Health, Real Estate, and Retail. The model is estimated using county-level data from 2011 to 2023, capturing both spatial and temporal variation in wildfire and smoke exposure over this period.

## 6.2 Amenities

Plugging household demand into equation (8), the equilibrium number of firms in each sector-location pair $(s, j)$ can be expressed as a function of local population composition and expenditures. Rearranging and taking logs yields:

$$\log N_{sjt} = -\log F_{sjt}(N_{jt}) + \log \left( \sum_k \beta_s^k X_{jt}^k \right), \tag{12}$$

where $N_{sjt}$ is the number of firms in sector $s$, county $j$, and year $t$; $N_{jt}$ is the total number of firms in that county; and $X_{jt}^k \equiv \phi_k w_k^t M_{jt}^k$ is the total amenity expenditure by household type $k$. The parameters $\beta_s^k = \alpha_s^k / \sigma_s$ summarize how type-$k$ households' spending influences entry in each amenity sector $s$, weighted by their sectoral demand intensity and substitution elasticity.

We parameterize the fixed operating cost as a function of local business conditions:

$$F_{sjt}(N_{jt}) = \Lambda_j \Lambda_t R(N_{jt}) \Omega_{sjt}, \tag{13}$$

where $\Lambda_j$ and $\Lambda_t$ capture location- and year-specific cost shifters, $\Omega_{sjt}$ represents remaining unobserved shocks to operating costs, and $R(N_{jt})$ denotes the rental cost of commercial real estate. Following Almagro and Domínguez-Iino (2025), we assume that commercial rents increase with local firm density as

$$R(N_{jt}) = N_{jt}^{\eta}, \tag{14}$$

where $\eta$ is the inverse elasticity of supply of commercial space (an approach similar to Couture et al. (2024). Substituting this cost function into equation (12) gives the estimating equation:

$$\log N_{sjt} = \lambda_j + \lambda_t - \eta \log N_{jt} + \log \left( \sum_k \beta_s^k X_{jt}^k \right) + \omega_{sjt}, \tag{15}$$

where $\lambda_j = -\log \Lambda_j$, $\lambda_t = -\log \Lambda_t$, and $\omega_{sjt} = -\log \Omega_{sjt}$ capture unobserved location, time, and sectoral factors.

Equation (15) is the empirical specification we estimate. It relates the number of firms supplying amenity sector $s$ to local household demand, total firm activity, and location-specific business conditions. The dependent variable, $\log N_{sjt}$, is observed at the county-year level from 2021–2023, while the household composition and expenditure terms $X_{jt}^{k}$ are constructed from demographic microdata.

Households are divided into four income-based groups, and the amenity sectors include accommodation/food, education, health, real estate, and retail. This specification allows us to capture how income heterogeneity and migration dynamics—shaped in part by wildfire and smoke exposure—affect local amenity provision.

Following Couture et al. (2024), we solve our fully estimated model for $\eta$ equal to 1.3, which is based on the range of supply elasticities reported by Saiz (2010). We choose $\eta = 1.3$, corresponding to a housing supply elasticity of 0.75. Saiz (2010) estimate of elasticity in San Fransisco is 0.66.

### 6.2.1 Identification.

The main identification challenge in estimating $\beta_{s}^{k}$ from equation (15) arises from simultaneity between amenity supply and household composition. The expenditure term $X_{jt}^{k}$ for a given location is the outcome of residential choices that depend on the existing amenity mix $N_{sjt}$. Consequently, any unobserved supply-side shock $\omega_{sjt}$ affecting firm entry will also influence $M_{jt}^{k}$ (and thus $X_{jt}^{k}$) in equilibrium. Because $\omega_{sjt}$ represents an amenity supply shock, we require instruments that shift amenity demand exogenously.

To address this, we construct an instrument that shifts population composition, and therefore amenity demand, differentially across sectors. Instead of using the stock of housing units by tenancy status as in Almagro and Domínguez-Iino (2025), we use the distribution of housing stock by household age group, as defined earlier in the analysis. Specifically, let $S_{jt}^{a}$ denote the number of housing units occupied by households whose head belongs to age group $a \in \{< 35, \text{35-50}, \text{50-65}, > 65\}$. We then interact these age-specific housing stocks with the group-specific mean income $w_{t}^{a}$, constructing the following demand shifter:

$$Z_{jt}^{a} = w_{t}^{a}\, S_{jt}^{a}. \tag{16}$$

The intuition behind this relevance condition is that counties with a greater concentration of older households (e.g., age more than 50 years) are more likely to experience higher expenditure shares on health amenities, while younger areas (e.g., less than 35 years) exhibit higher demand for accommodation/food services. This variation in age composition thus induces exogenous shifts in the demand for specific amenity sectors.

In addition, we plan to use exposure to wildfire smoke as an instrumental variable. Higher smoke exposure is expected to alter the demographic composition of neighborhoods by influencing household mobility and sorting decisions. Since smoke primarily affects firms indirectly, through its impact on population and demand rather than direct operational constraints, it is unlikely to be correlated with the unobserved determinants of amenity supply.

Our exclusion restriction is expressed as:

$$E[Z^a_{jt}\,\omega_{sjt} \mid \lambda_j, \lambda_t] = 0, \tag{17}$$

which allows for locations with different age compositions to have distinct baseline commercial cost structures (e.g., higher commercial rents in older, wealthier areas) but assumes that age composition is uncorrelated with the changes in unobserved fixed costs. For instance, while older counties may have systematically higher business rents, the exclusion restriction would be violated only if demographic aging were directly correlated with evolving local policies or zoning changes that alter firm operating costs. Under this assumption, variation in age-based household composition provides valid exogenous shifts in amenity demand that help identify the sectoral responsiveness parameters $\beta^k_s$.

#### 6.2.2 Interpretation of $\beta^k_s$ Parameters

The estimated parameters $\beta^k_s$ measure how strongly the expenditures of each household type influence the supply of firms in sector $s$. Larger $\beta^k_s$ values indicate stronger feedback between household demand and amenity provision—for example, a large $\beta^k_s$ in the health sector for high-income or older households implies that their migration and spending significantly drive the entry of new health-related firms.

Conversely, small or statistically insignificant coefficients suggest sectors less responsive to demographic shifts, such as education, where supply is often publicly determined.

These feedback effects explain persistent sorting patterns and structural change in local economies following climate shocks such as wildfires. Counties that attract older, wealthier households after smoke events experience a reallocation of firms toward health, real estate, and retail sectors, while younger and lower-income inflows sustain food and accommodation services. In this way, the endogeneity of amenities magnifies spatial inequality, as shifts in household composition reshape local production structures and reinforce differences in economic opportunity.

#### 6.2.3 Implementation

We use five amenity sectors that provide local services: Accommodation and Restaurants, Education, Health, Real Estate, and Retail. We simultaneously estimate the parameters in equation (15) for all sectors using the Generalized Method of Moments (GMM).

To construct our moments, we interact the instruments with sector dummies such that $Z^k_{sjt} = \mathbb{1}_s Z^k_{jt}$, where $\mathbb{1}_s$ equals one if the observation belongs to sector $s$. We then combine $Z^k_{sjt}$ with the residual $\omega_{sjt}$ from equation (15) to define the moment function $g^k_s(\lambda_j, \lambda_t, \beta^k_s)_{sjt} = Z^k_{sjt}\,\omega_{sjt}$. The corresponding moment conditions identifying $\beta^k_s$ are

$$E\big[g^k_s(\lambda_j, \lambda_t, \beta^k_s)_{sjt}\big] = 0. \tag{18}$$

The location and time fixed effects are identified through the following additional conditions:

$$E[\lambda_j\,\omega_{sjt}] = 0, \qquad E[\lambda_t\,\omega_{sjt}] = 0. \tag{19}$$

Stacking all moment conditions yields the system

$$E\big[g(\lambda_j, \lambda_t, \beta^k_s)_{sjt}\big] = E[Z_{sjt}\,\omega_{sjt}] = 0, \tag{20}$$

where $Z_{sjt} = [Z^1_{sjt}, Z^2_{sjt}, Z^3_{sjt}, Z^4_{sjt}, \lambda_j, \lambda_t]_{s,j,t}$ collects the instruments for all household types.

To ensure a well-defined optimization problem, we impose the constraint $\beta^k_s \geq 0$ for all $s, k$, so that $\log(\sum_k \beta^k_s X^k_{jt})$ always exists. The $\beta^k_s$ parameters are proportional to the expenditure shares in the amenity demand model in Section **??**, which naturally have a nonnegative lower bound.

Finally, we solve the following constrained optimization problem:

$$\max_{\lambda_j, \lambda_t, \beta^k_s} \; \hat{g}(\lambda_j, \lambda_t, \beta^k_s)'\hat{W}\hat{g}(\lambda_j, \lambda_t, \beta^k_s) \quad \text{s.t.} \quad \beta^k_s \geq 0 \;\forall\, s, k, \tag{21}$$

where $\hat{W} = (Z'_{sjt} Z_{sjt})^{-1}$ is the optimal GMM weighting matrix.

#### 6.2.4 Results: Amenity Supply and Household Influence Across Sectors

Table 7 summarizes the estimated $\beta^k_s$ coefficients averaged across two dimensions: by sector and by household age group. The coefficients measure how strongly expenditures by households of type $k$ contribute to firm entry and amenity provision in sector $s$, based on the equilibrium relationship estimated from Equation 1. Standard errors (in parentheses) are obtained through bootstrapping.

The results show substantial variation in how different household groups influence local amenity provision. Across household types, the average $\beta$ coefficients increase with age, indicating that older households exert greater influence on local firms—consistent with their higher income and greater housing wealth. Households aged 50–65 display the largest average coefficients, implying that this group has the strongest effect on local service provision. From the sectoral perspective, education appears least sensitive to demographic composition, with a relatively low elasticity of 0.36, while the health and retail sectors are much more responsive to household shifts, with coefficients of 1.28 and 1.90, respectively. These results suggest that as older, higher-income households concentrate in certain areas, sectors such as health and retail expand disproportionately, while education services remain comparatively stable.

Table 7: Average Amenity Supply Coefficients by Sector and Household Age Group

| By Sector | | By Household Age | |
|---|---|---|---|
| Accommodation | 1.005 | <35 | 0.911 |
| | (0.091) | | (0.122) |
| Education | 0.357 | 35-50 | 0.857 |
| | (0.055) | | (0.181) |
| Health | 1.277 | 50-65 | 1.365 |
| | (0.134) | | (0.202) |
| Real Estate | 0.846 | >65 | 1.175 |
| | (0.091) | | (0.154) |
| Retail | 1.900 | | |
| | (0.199) | | |

*Notes:* Entries report the average $\beta_s^k$ coefficients, capturing how strongly household demand influences firm activity and amenity supply. Standard errors in parentheses are obtained via bootstrapping. Higher values indicate greater household influence on sectoral amenity provision or greater sectoral sensitivity to demographic composition.

Table 8 provides the full set of $\beta_s^k$ estimates by household age group and sector. The coefficients measure the relative contribution of each household type to amenity supply in each sector, with bootstrapped standard errors reported in parentheses.

The results reveal clear heterogeneity across sectors and household types. The real estate sector shows limited differentiation by age, suggesting that housing-related amenities respond similarly to demographic composition across groups. By contrast, the health sector depends strongly on older populations: coefficients are large and highly significant for households aged 50 and above, consistent with greater demand for healthcare services among these age groups. Retail activity is most responsive to changes in the 35–65 age range, reflecting the higher consumption intensity of middle-aged households. Education, meanwhile, shows minimal sensitivity to older households, indicating that shifts in age structure primarily affect other service sectors. Overall, these results suggest that demographic composition—particularly the presence of older, higher-income households—plays a central role in shaping the structure of local amenity-providing industries.

Table 8: Estimated Amenity Supply Parameters by Household Age and Sector

| | Accm/Food | Education | Health | Real Estate | Retail |
|---|---|---|---|---|---|
| <35 | 1.000*** | 0.411* | 0.601* | 0.993*** | 1.546*** |
| | (0.000) | (0.226) | (0.351) | (0.267) | (0.288) |
| 35–50 | 0.861*** | 0.131 | 0.315 | 0.722*** | 2.253*** |
| | (0.220) | (0.149) | (0.432) | (0.239) | (0.332) |
| 50–65 | 1.134*** | 0.609*** | 1.927*** | 0.891*** | 2.261*** |
| | (0.249) | (0.229) | (0.335) | (0.240) | (0.317) |
| >65 | 1.024*** | 0.275 | 2.263*** | 0.775*** | 1.536*** |
| | (0.240) | (0.228) | (0.524) | (0.232) | (0.298) |

*Notes:* Coefficients ($\beta_s^k$) represent the relative strength of the relationship between household demand of type $k$ and firm activity in sector $s$. Standard errors (in parentheses) are derived from bootstrapping. Higher coefficients indicate greater influence of the household group on sectoral amenity supply.

## 6.3 Housing Demand

The econometric implementation of the model estimate the parameters of interest. The probability that household $i$ chooses housing type $h$ at time $t$ is given by:

$$P_{ht}^i = \frac{\exp\left(\delta_{ht} + \lambda_{ht}^i\right)}{\sum_k \exp\left(\delta_{kt} + \lambda_{kt}^i\right)} \tag{22}$$

The likelihood function for the model is constructed as:

$$L = \sum_T \sum_I \sum_H \left(I_{ht}^i \ln(P_{ht}^i)\right) \tag{23}$$

Estimation proceeds in two steps. In the first step, maximum likelihood estimation (MLE) and contraction mapping are used to estimate the heterogeneous parameters in $\lambda_{ht}^i$ and the mean indirect utilities ($\delta_{ht}$). In the second step, the mean indirect utilities are regressed on the observed characteristics of the property types:

$$\delta_{ht} = \alpha_{0X} X_{ht} + \alpha_{0p} p_{ht} + \alpha_{0F} A_{ht} + \alpha_{0S} S_{ht} + \xi_{ht} \tag{24}$$

This step estimates the mean preference parameters ($\alpha_{0j}$) while addressing endogeneity concerns through property type fixed effects and instrumental variables (IVs).

#### 6.3.1 Challenges in Estimation

The second stage of estimation faces two primary challenges. First, smoke exposure ($S_{ht}$) is likely correlated with unobserved utility ($\xi_{ht}$). To address this, we rely on the temporal variation in smoke exposure, which is assumed to be quasi-random. Second, property prices ($p_{ht}$) may also be correlated with $\xi_{ht}$. To mitigate this, we employ donut instrumental variables (IVs) that exploit spatial variation in prices while excluding nearby properties that may share unobserved characteristics. We use the mean price of the properties in the 1-mile rings at distances of 4, 5, 6, and 7 miles.

#### 6.3.2 Model Details

We estimate a static household location choice model using household-level data from DataAxle for the 10-year period from 2014 to 2023. From the full dataset, we randomly select approximately 12% of households from each year to form a representative sample. Each household (agent) chooses a location—defined at the sub census tract level—where to live in a given year.

Within each tract and year, properties are sorted into price quantiles to capture within-tract variation in housing costs and attributes. On the demographic side, we use a continuous measure of the age of the household head, normalized by the mean age. Our key environmental variable is the normalized mean seasonal smoke concentration at the tract-year level. Based on the reduced-form results (see Table 3), we use a two-year lag of smoke exposure, as the largest effects on property values are observed with a two-year delay.

We also include measures of local amenities provided by firms. Specifically, we use the log count of firms supplying local amenities (such as accommodation, restaurants, retail, and health services) and non-local amenities (such as manufacturing, management, and technology-related sectors). These amenity measures are aggregated at the city and county levels, as households are likely to value access to services available within a reasonable travel distance beyond their own census tract.

The final estimation sample includes approximately 3.5 million household-year observations. Each household chooses among roughly 2,300 potential locations, taking into account housing prices, local amenities, and exposure to smoke when deciding where to live.

#### 6.3.3 Model Results

The results, summarized in Table 9, show substantial heterogeneity in households' willingness to pay to avoid smoke exposure. The average marginal willingness to pay (MWTP) to avoid one standard deviation of mean seasonal smoke (lagged two years) is 3.2% of the property value. Older households display a stronger aversion to smoke, with MWTP increasing steadily with age. Households headed by individuals over 65 are willing to pay about 4% of the property value to avoid such exposure, while those aged 50–65 exhibit an MWTP of roughly 3.4%. In contrast, younger households (under 35) are less responsive, with an MWTP of around 2.5%. These differences align with greater health vulnerability and risk sensitivity among older households and indicate meaningful demographic sorting in response to environmental hazards such as wildfire smoke.

Table 9: Estimated Mean MWTP to Avoid One Standard Deviation of Mean Seasonal Smoke (Lagged Two Years)

| **Household Group** | **MWTP (% of Property Value)** |
|---|---|
| **All Households** | 3.21 |
| *By Age of Household Head* | |
| Less than 35 | 2.45 |
| 35-50 | 2.88 |
| 50-65 | 3.40 |
| More than 65 | 4.00 |

*Notes:* This table reports the estimated mean marginal willingness to pay (MWTP) to avoid one standard deviation of mean seasonal smoke exposure, lagged by two years. Estimates are expressed as percentages of property value. Values are derived from the coefficient on log price in the structural household sorting model. The MWTP rises with age, indicating that older households exhibit a greater aversion to smoke exposure.

# 7 Conclusions

This paper documents the long-run demographic and economic adjustments induced by wildfire and smoke exposure and develops a general-equilibrium framework to interpret their welfare implications. Using detailed household- and firm-level data from 2011-2023, we show that both wildfire and smoke exposures generate persistent population and firm losses, with smoke having far more pervasive and enduring effects. Smoke exposure leads to substantial out-migration among older households and modest inflows of younger ones, producing measurable shifts in neighborhood composition. These demographic adjustments, in turn, reshape local economic structure: sectors serving older or higher-income populations contract, while those catering to younger residents or essential services exhibit relative resilience.

Our structural model highlights that these joint household and firm responses create feedback loops that amplify the spatial and welfare consequences of environmental risk. Endogenous amenity responses magnify disparities across neighborhoods, as declining demand and firm exit reduce local amenities and further lower the attractiveness of exposed areas. Welfare losses are substantial and unevenly distributed, with older households and homeowners bearing the largest burdens. Counterfactual simulations indicate that policies reducing smoke exposure—through improved fire management or air quality interventions—could yield sizable welfare gains, particularly in communities with aging populations.

Taken together, the results demonstrate that environmental risks such as wildfire smoke not only threaten health and property but also alter the demographic and industrial geography of local economies. Accounting for these general-equilibrium feedbacks is essential for accurately assessing the long-run welfare and distributional impacts of climate-related hazards and for designing adaptation policies that mitigate both their immediate and persistent economic effects.

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# A Appendix Figures

## A.1 Wildfire Trends

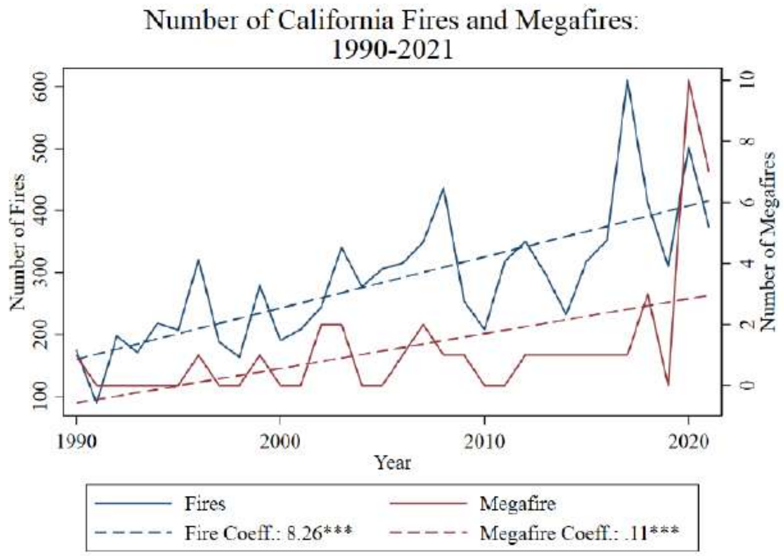



Figure A1: Count of California fires and megafires in the last three decades

*Source:* Wang (2024)
*Note:* The original data source is CAL FIRE. The graph shows an increase in the instances of both fires and mega-fires in California since 1990.

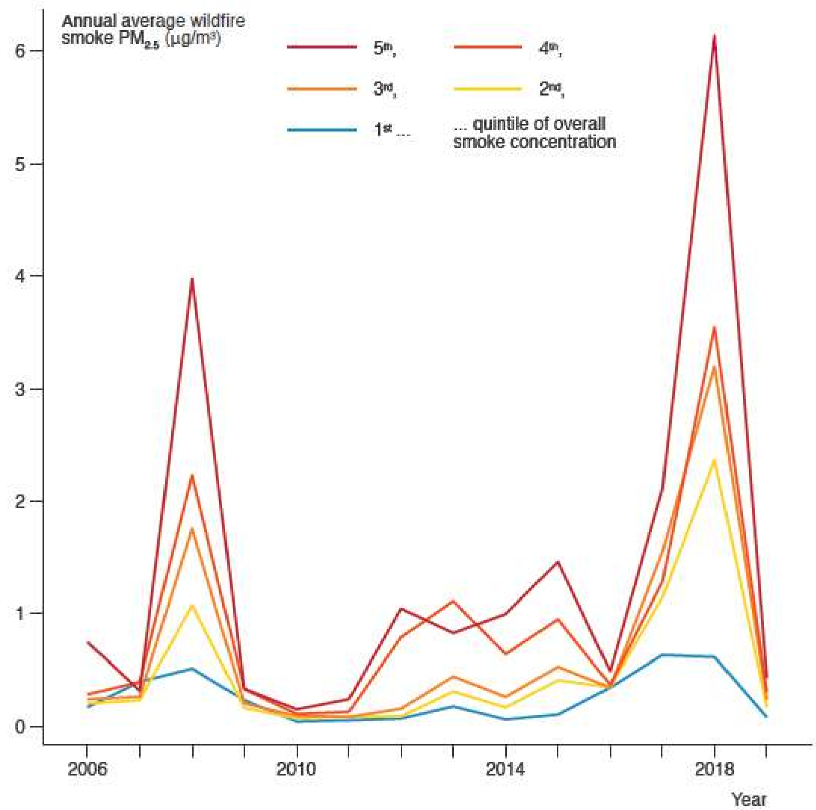



Figure A2: Average annual smoke by quintile of overall distribution

*Source:* Knittel and Krebs (2024)
*Note:* Annual average wildfire smoke $PM_{2.5}$ concentration in $\mu g/m^3$ for five quintiles of the 2006–2019 average smoke concentration.

## A.2 Spatial Distribution

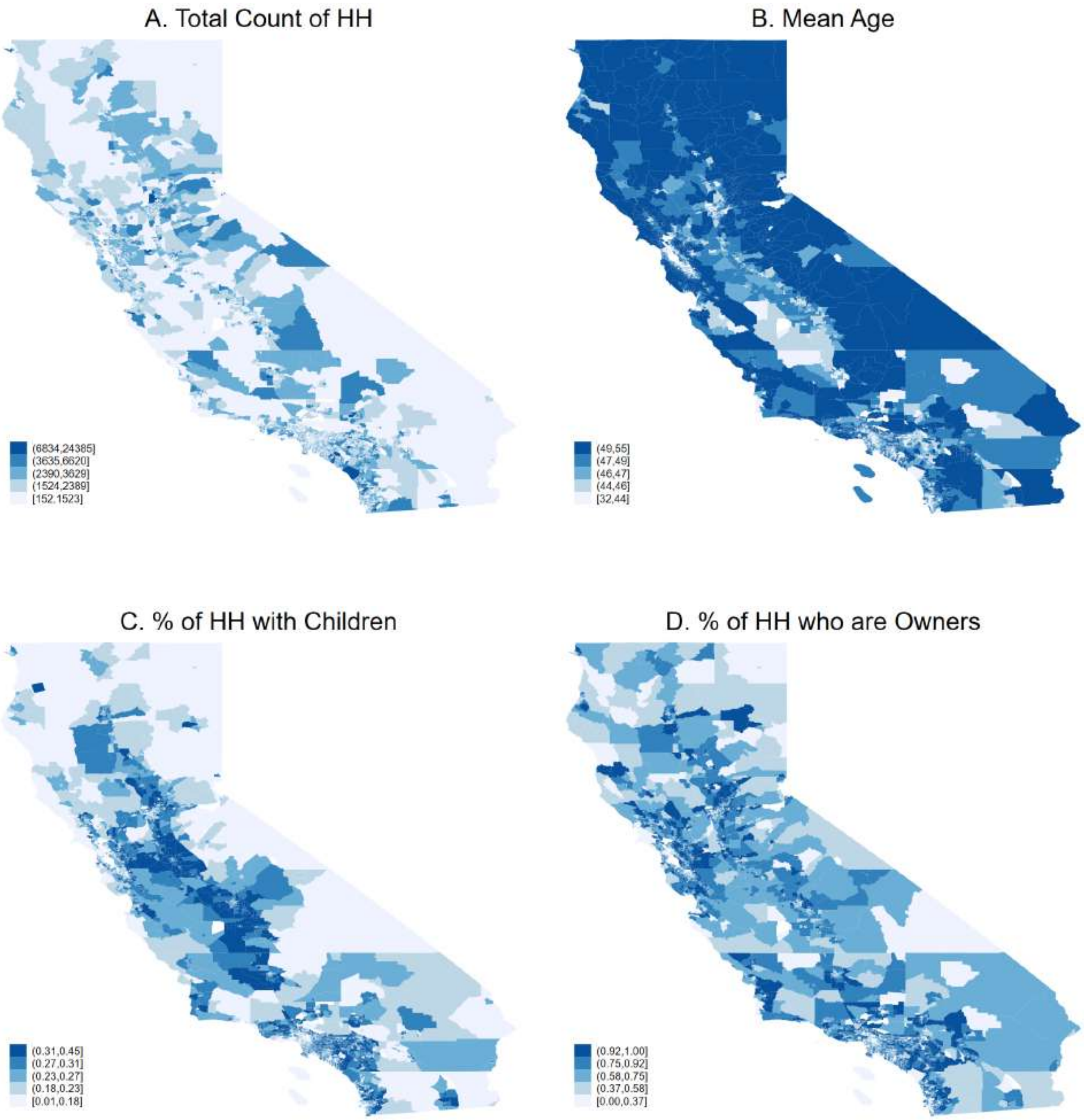



Figure A3: Tract level household attributes in 2017

*Note:* The set of maps shows tract-level household attributes for 2017. The top two maps depict the total household count per tract and the average age of residents. The mean age tends to be lower in and around urban areas. The bottom two maps show the percentage of households with children and the percentage of owner-occupied households.
Source of the data is Data Axle Consumer Data

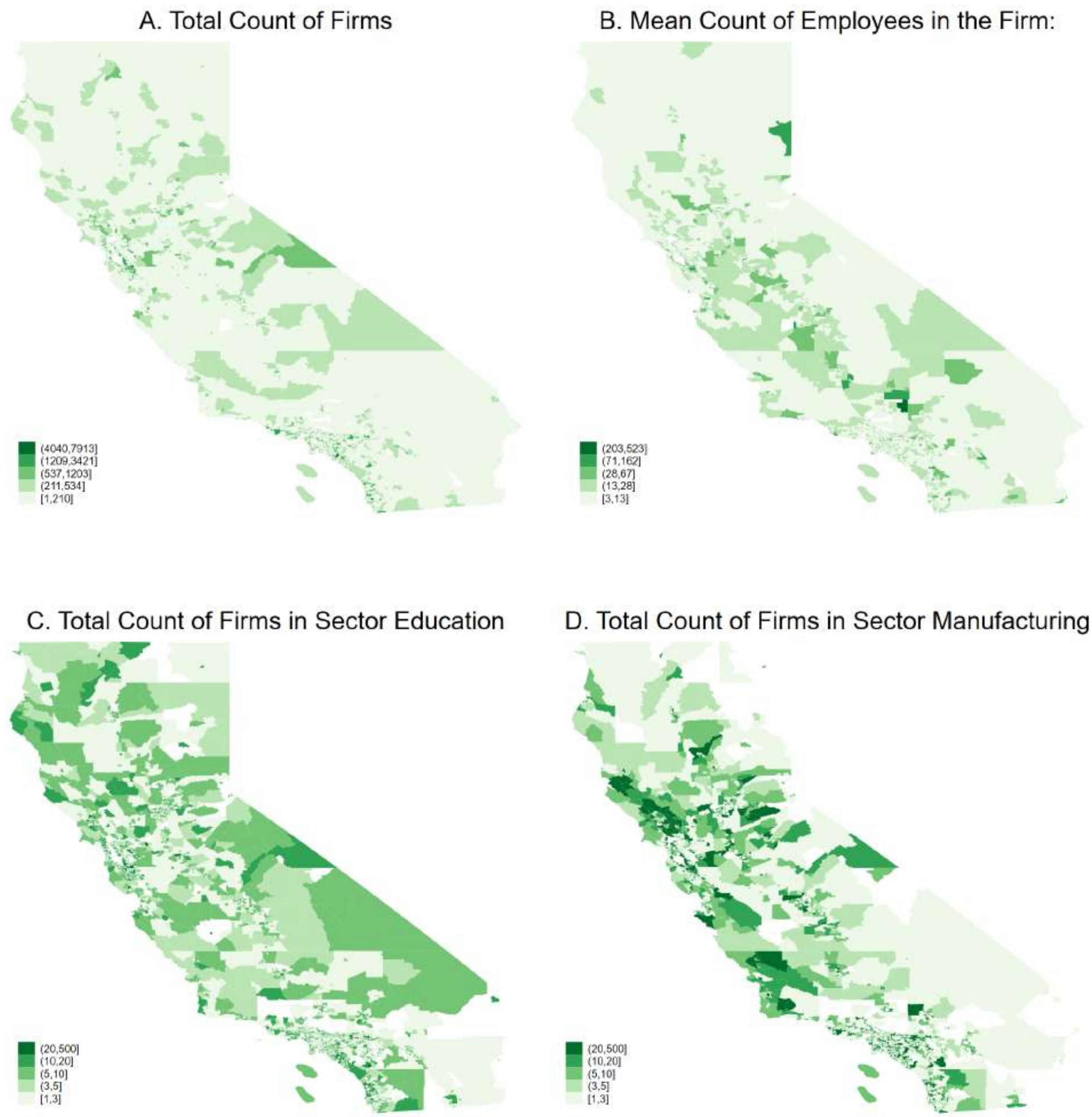
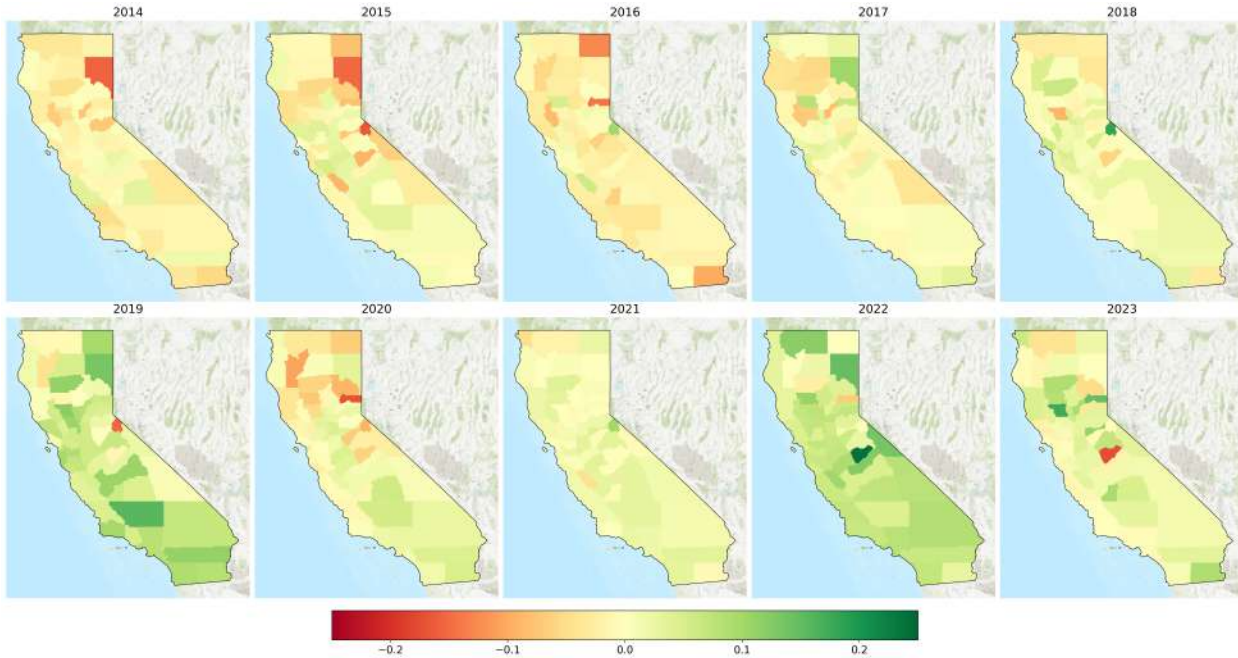
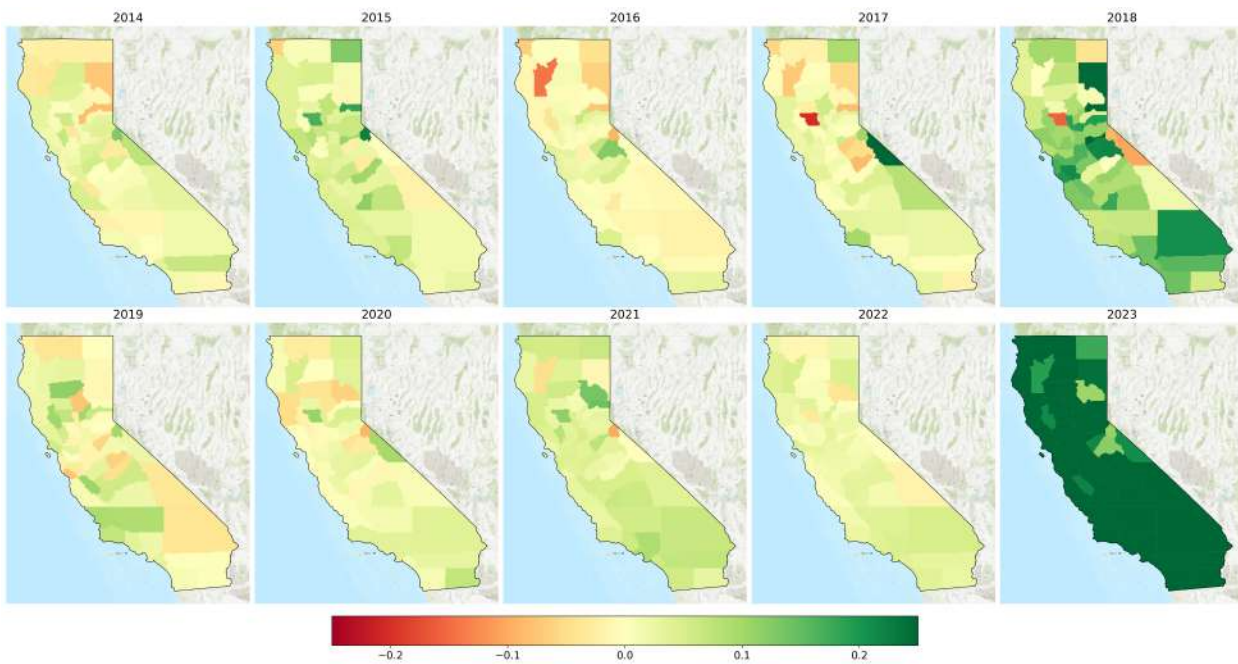



Figure A4: Tract level firm attributes in 2017

*Note:* The set of maps shows tract-level firm attributes for 2017. The top two maps depict the total number of firms per tract and the average number of employees per firm, which measures firm size. Most tracts are dominated by smaller firms, with an average of fewer than 28 employees. The bottom two maps compare firm counts in the education and manufacturing sectors. While the median and mean firm counts for these sectors are similar, the education sector is more evenly distributed, as indicated by consistent shades of green. In contrast, manufacturing firms are more clustered, with tracts exhibiting a mix of light and very dark green shades.
Source of the data is Data Axle Firm Data



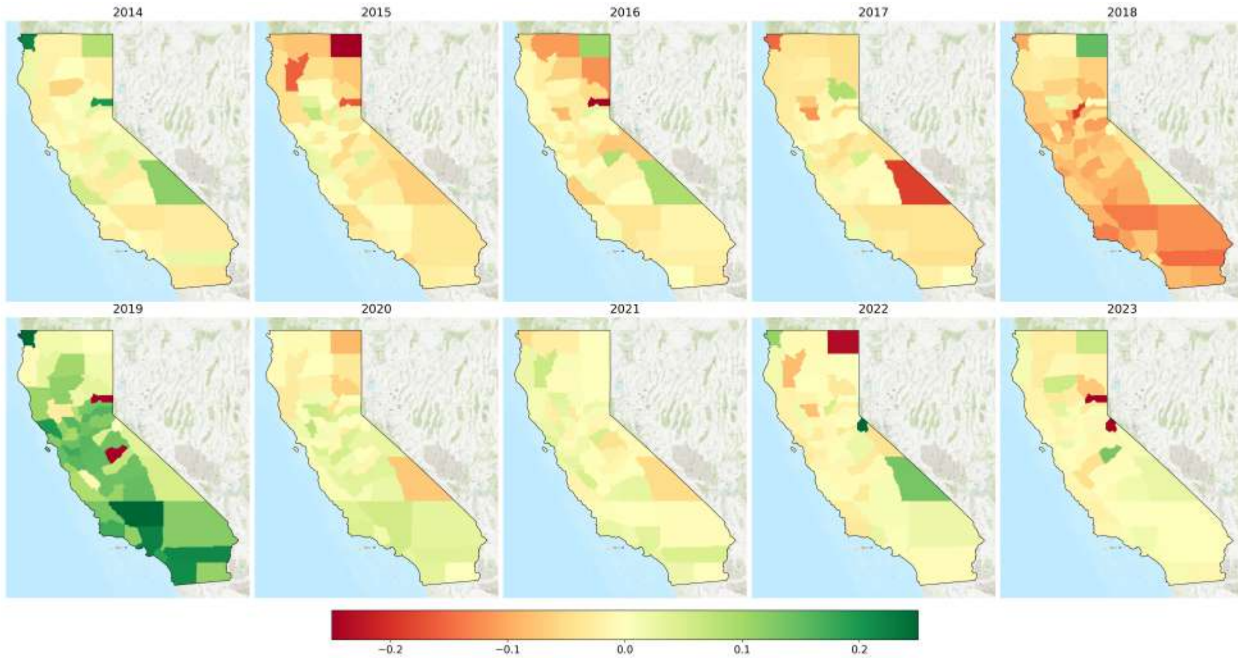

(a) Accommodation and restaurant sector, 2014–2023.



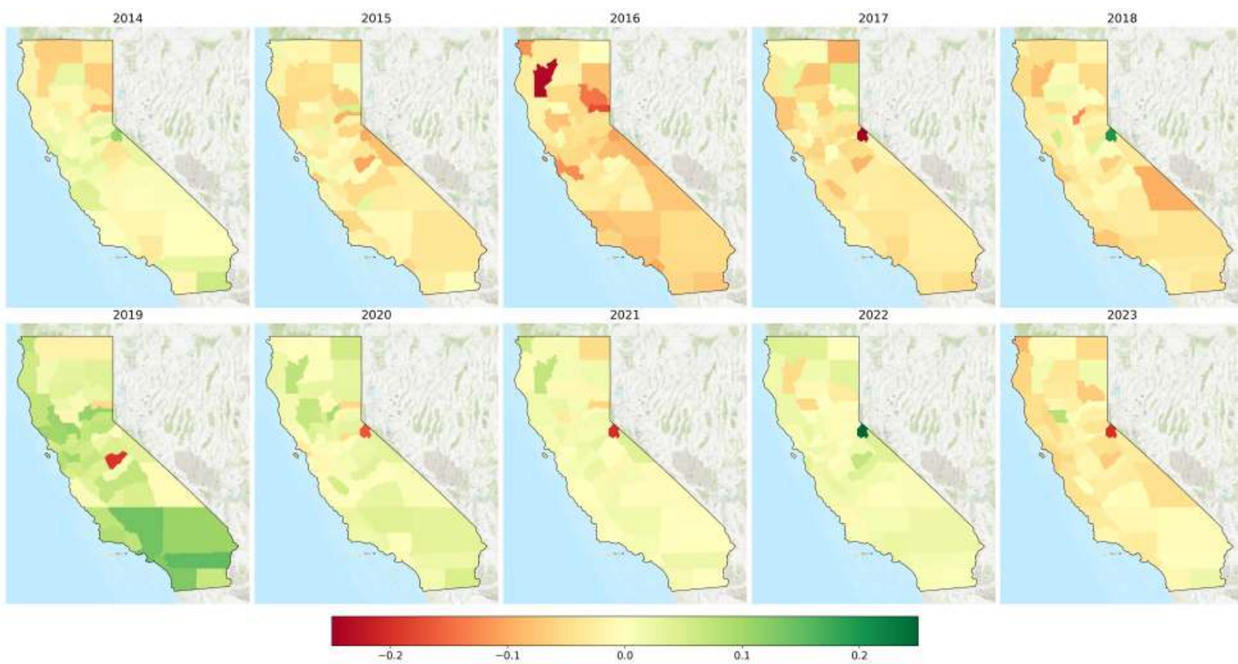

(b) Education sector, 2014–2023.

Figure A5: County-level percentage change in firm counts for (a) accommodation and restaurants and (b) health sectors, 2014–2023.

*Note:* Red indicates a decline and green an increase in firm counts, with darker shades reflecting larger magnitudes of change. The maps highlight distinct sectoral patterns across regions.




(a) Real estate sector, 2014–2023.




(b) Retail sector, 2014–2023.

Figure A6: County-level percentage change in firm counts for (a) health care and (b) real estate sectors, 2014–2025.

*Note:* Red indicates a decrease and green an increase in firm counts, with darker shades representing larger magnitudes of change. These sectors also exhibit substantial spatial variation, reflecting differences in local demand and service provision across regions.

## A.3 Data Reliability

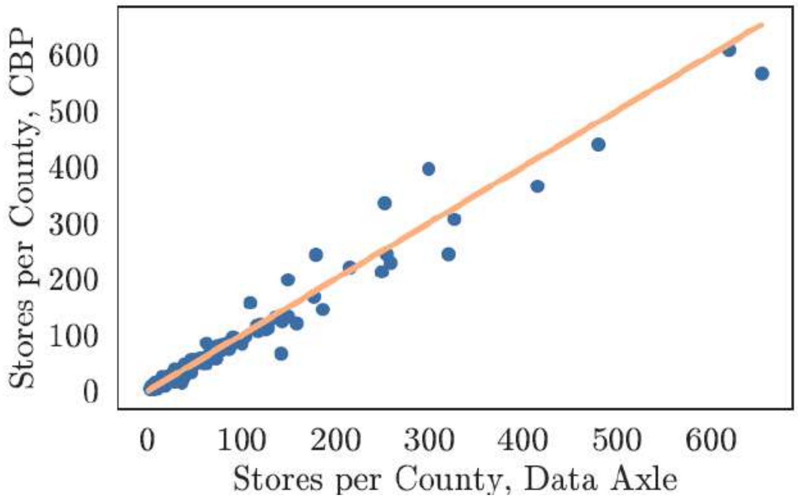
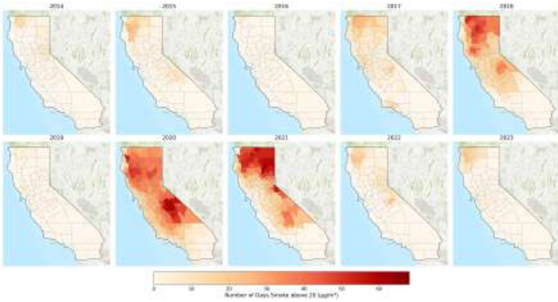


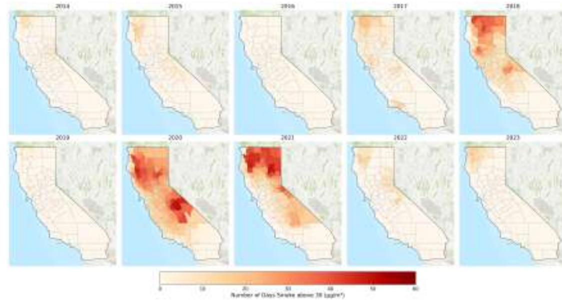

Figure A7: Count of stores from Data Axle and County Business Patterns (CBP) in 2019.

*Source:* Cao et al. (2024)
*Note:* To assess the reliability of the Data Axle firm data, Cao et al. (2024) compare county-level store counts derived from Data Axle for NAICS code 452 with the corresponding store counts from the U.S. Census Bureau's County Business Patterns (CBP) data. The results show that the county-level store counts from Data Axle are highly consistent with those from the CBP.

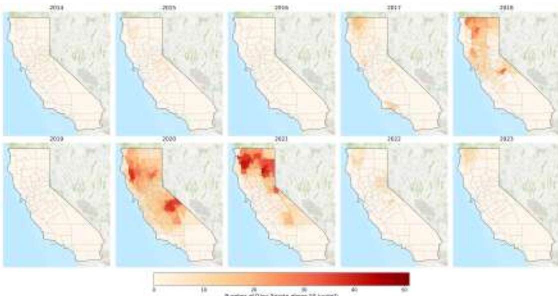
## A.4 Different Measures of Smoke Exposure



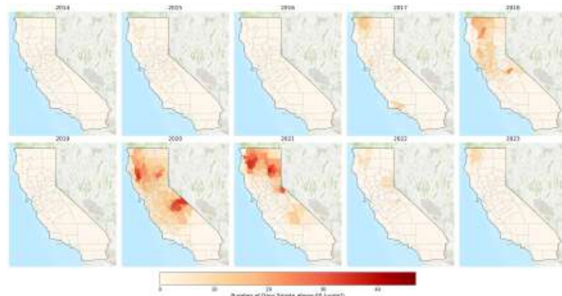
(a) Number of days smoke above 20 $\mu g/m^3$



(b) Number of days smoke above 30 $\mu g/m^3$



(c) Number of days smoke above 50 $\mu g/m^3$



(d) Number of days smoke above 60 $\mu g/m^3$

Figure A8: Annual number of days with $PM_{2.5}$ concentrations above different thresholds at the census-tract level, 2014-2023.

Note: Each panel shows the number of days per year with $PM_{2.5}$ levels exceeding the indicated threshold. Darker red shades indicate more frequent exposure (i.e., more days above the pollution threshold)

# B Appendix Tables

## B.1 Robustness

### B.1.1 Robustness: Count of Households

Table B1: Robustness of Household Count Effects to Alternative Exposure Measures

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A. Alternative Measures of Wildfire Exposure** | | | | |
| | Burned Area | Burned Area Within | | |
| | | 1 mile | 5 miles | 10 miles |
| Wildfire lag 1 | -0.00029 | -0.00132*** | -0.00098*** | -0.00046 |
| | (0.0005) | (0.0003) | (0.0003) | (0.0004) |
| Wildfire lag 2 | -0.00008 | -0.00149*** | -0.00089** | -0.00047 |
| | (0.0005) | (0.0003) | (0.0004) | (0.0004) |
| Wildfire lag 3 | 0.00032 | -0.00163*** | -0.00077** | -0.00035 |
| | (0.0005) | (0.0004) | (0.0004) | (0.0004) |
| Smoke lag 1 | -0.00163*** | -0.00153*** | -0.00152*** | -0.00159*** |
| | (0.0004) | (0.0004) | (0.0004) | (0.0005) |
| Smoke lag 2 | -0.00335*** | -0.00324*** | -0.00324*** | -0.00327*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Smoke lag 3 | -0.00173*** | -0.00153*** | -0.00157*** | -0.00161*** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Observations | 61,939 | 61,939 | 61,939 | 61,939 |
| Adjusted $R^2$ | 0.97 | 0.97 | 0.97 | 0.97 |
| **Panel B. Alternative Measures of Smoke Exposure** | | | | |
| | Seasonal Mean | Days > 30 | Days > 40 | Days > 50 |
| Wildfire lag 1 | -0.00131*** | -0.00132*** | -0.00133*** | -0.00134*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Wildfire lag 2 | -0.00154*** | -0.00149*** | -0.00149*** | -0.00151*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| Wildfire lag 3 | -0.00165*** | -0.00163*** | -0.00162*** | -0.00165*** |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| Smoke lag 1 | -0.00247*** | -0.00153*** | -0.00128*** | -0.00112*** |
| | (0.0006) | (0.0004) | (0.0004) | (0.0004) |
| Smoke lag 2 | -0.00381*** | -0.00324*** | -0.00291*** | -0.00261*** |
| | (0.0006) | (0.0005) | (0.0004) | (0.0004) |
| Smoke lag 3 | -0.00200*** | -0.00153*** | -0.00149*** | -0.00119*** |
| | (0.0006) | (0.0005) | (0.0005) | (0.0004) |
| Observations | 61,939 | 61,939 | 61,939 | 61,939 |
| Adjusted $R^2$ | 0.97 | 0.97 | 0.97 | 0.97 |

*Notes:* Each panel reports estimates from Specification (3) of Table 1. The dependent variable is the log of the count of households at the census tract level. In Panel A, smoke exposure is fixed to annual days with $PM_{2.5} > 40$ $\mu g/m^3$, while wildfire exposure varies by spatial radius around the tract centroid. In Panel B, wildfire exposure is fixed to the area burned within one mile, while smoke exposure varies by intensity measure. All exposure variables are normalized to have a mean of zero and a unit standard deviation. Standard errors, clustered at the tract level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

### B.1.2 Robustness: Count of Firms

Table B2: Robustness of the Effects of Wildfire and Smoke Exposure on Firm Counts

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A. Alternative Measures of Wildfire Exposure** | | | | |
| | Burned Area | Burned Area Within | | |
| | | 1 mile | 5 miles | 10 miles |
| Wildfire lag 1 | -0.00037 | -0.00030 | 0.00041 | 0.00096** |
| | (0.0005) | (0.0005) | (0.0004) | (0.0005) |
| Wildfire lag 2 | 0.00069 | -0.00024 | 0.00037 | 0.00098** |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Wildfire lag 3 | 0.00039 | -0.00084* | -0.00042 | 0.00023 |
| | (0.0006) | (0.0005) | (0.0005) | (0.0005) |
| Smoke lag 1 | -0.00908*** | -0.00916*** | -0.00927*** | -0.00938*** |
| | (0.0006) | (0.0005) | (0.0006) | (0.0006) |
| Smoke lag 2 | -0.01532*** | -0.01516*** | -0.01526*** | -0.01541*** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Smoke lag 3 | -0.01379*** | -0.01361*** | -0.01359*** | -0.01371*** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0006) |
| Observations | 48,818 | 48,818 | 48,818 | 48,818 |
| Adjusted $R^2$ | 0.98 | 0.98 | 0.98 | 0.98 |
| **Panel B. Alternative Measures of Smoke Exposure** | | | | |
| | Seasonal Mean | Days > 30 | Days > 40 | Days > 50 |
| Wildfire lag 1 | -0.00035 | -0.00030 | -0.00026 | -0.00028 |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Wildfire lag 2 | -0.00039 | -0.00024 | -0.00013 | -0.00013 |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Wildfire lag 3 | -0.00109** | -0.00084* | -0.00074 | -0.00075 |
| | (0.0005) | (0.0005) | (0.0005) | (0.0005) |
| Smoke lag 1 | -0.01216*** | -0.00916*** | -0.00863*** | -0.00839*** |
| | (0.0007) | (0.0005) | (0.0005) | (0.0005) |
| Smoke lag 2 | -0.01886*** | -0.01516*** | -0.01467*** | -0.01434*** |
| | (0.0007) | (0.0006) | (0.0005) | (0.0005) |
| Smoke lag 3 | -0.01623*** | -0.01361*** | -0.01314*** | -0.01268*** |
| | (0.0008) | (0.0006) | (0.0006) | (0.0006) |
| Observations | 48,818 | 48,818 | 48,818 | 48,818 |
| Adjusted $R^2$ | 0.98 | 0.98 | 0.98 | 0.98 |

*Notes:* Each panel reports estimates from Specification (3) of Table 4. The dependent variable is the log of the count of firms at the census tract level. In Panel A, smoke exposure is fixed to annual days with $PM_{2.5} > 40$ $\mu g/m^3$, while wildfire exposure varies by spatial radius around the tract centroid. In Panel B, wildfire exposure is fixed to the area burned within one mile, while smoke exposure varies by intensity measure. All exposure variables are normalized to have a mean of zero and a unit standard deviation. Standard errors, clustered at the tract level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

### B.1.3 Robustness: Heterogeneous Effects by Firm Size (Employment)

Table B3: Heterogeneous Effects of Wildfire and Smoke Exposure by Firm Size (Employment)

| | <20 | 20–100 | 100–500 | >500 |
|---|---|---|---|---|
| Wildfire lag 1 | -0.00077* | -0.00101 | -0.00088 | -0.00251 |
| | (0.0004) | (0.0008) | (0.0014) | (0.0025) |
| Wildfire lag 2 | -0.00070 | -0.00088 | 0.00067 | -0.00301 |
| | (0.0005) | (0.0009) | (0.0015) | (0.0026) |
| Wildfire lag 3 | -0.00112** | -0.00092 | 0.00128 | -0.00005 |
| | (0.0005) | (0.0009) | (0.0015) | (0.0027) |
| Smoke lag 1 | -0.00506*** | 0.00255** | 0.00204 | 0.00771** |
| | (0.0005) | (0.0010) | (0.0017) | (0.0031) |
| Smoke lag 2 | -0.01049*** | -0.00086 | 0.00158 | 0.00907*** |
| | (0.0005) | (0.0010) | (0.0017) | (0.0032) |
| Smoke lag 3 | -0.01053*** | -0.00474*** | -0.00323* | 0.00858*** |
| | (0.0006) | (0.0011) | (0.0018) | (0.0033) |
| Observations | 48,818 | 48,688 | 37,519 | 10,033 |
| Adjusted $R^2$ | 0.98 | 0.96 | 0.92 | 0.84 |

*Notes:* The dependent variable is the log count of firms in each size category based on the number of employees. All models include tract and year fixed effects. Standard errors, clustered at the tract level, are reported in parentheses. Coefficients represent the percent change in firm counts caused by a one standard deviation increase in exposure. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.