The Distribution and Consequences of Disaster Property Losses: Evidence from Tax Returns of Wildfire Victims

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Abstract

We merge property-level damage data for over 100 U.S. wildfires with individual tax and Census data to understand (i) the demographics of the wildfire-exposed population and (ii) the effects of wildfires on post-event earnings, employment, and migration for affected individuals and communities. On average, occupants of wildfire-exposed homes are wealthier and more likely to be white than the US population. Conditional on a fire occurring, homes occupied by lower-income individuals are more likely to be destroyed, consistent with other evidence of a "structure vulnerability gap". Wildfires reduce earnings for occupants of destroyed homes for three years after the event, with earnings losses peaking at 10% in year 1. Unlike Hurricane Katrina, there is no evidence that wildfire events increase long-run earnings for affected individuals, and no evidence of higher post-event earnings among individuals who choose to migrate away following the fire. Four year after a wildfire, 50% of burned homes remain unoccupied and the average income for occupants of rebuilt homes is substantially above the pre-fire average.

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1 Introduction

Global economic losses from natural catastrophes totaled $320 billion in 2024, continuing a trend of increasing costs.[1] Adapting to these growing perils requires an understanding of the broader economic consequences of disasters as well as how these impacts are distributed. We provide new information for catastrophic wildfire events in the United States. We merge address-level damage data for more than 100 U.S. wildfires representing 70% of wildfire-exposed homes over two decades with individual tax returns and Census microdata to reveal detailed demographics of wildfire-affected households and the effects of wildfire events on earnings, employment, and migration in subsequent years. The highly granular damage data allow us to separately examine occupants of destroyed homes, homes that were exposed to the fire but were not destroyed, and unexposed homes located near the area of the fire.

Our first main contribution is a set of descriptive analyses on the distribution of hazard and vulnerability. We document disparities in wildfire *hazard* by comparing the income, race, ethnicity, and age of the occupants of wildfire-affected (destroyed and surviving) homes to the US population and to nearby unaffected populations. The second descriptive exercise examines disparities in structure *vulnerability* conditional on exposure to a wildfire. These analyses compare demographics for the occupants of destroyed vs. surviving homes. Understanding these demographic patterns of hazard and vulnerability is crucial for designing and evaluating risk mitigation initiatives and post-disaster assistance programs.

Our second main contribution is to estimate the causal effects of wildfire on income, employment, and migration for affected individuals in the several years following the wildfire. Our empirical strategy compares three groups of individuals. The first group are people whose homes were destroyed in the wildfire, "wildfire victims". The second group are people whose homes were inside the wildfire perimeter but that survived the wildfire (henceforth, "surviving homes"). We

1. Munich RE, "Natural Disasters in 2024", January 2025.

compare both groups to various comparison sets of households located away from the wildfire-affected area.

Finally, we also contribute new descriptive evidence on how neighborhood composition – e.g., occupant income and age – changes following a destructive wildfire. These new summary statistics speak to questions of "post-disaster gentrification".

A key advantage of our study is the ability to precisely observe the level of property damage experienced by each individual resident. Previous studies of the financial consequences of floods, storms, and tornadoes proxy for individual damages with average damages by zip code or Census geography.[2] This aggregation may obscure the detailed relationship between realized property losses and household financial consequences. Both flood damages (Hovekamp and Wagner 2023) and wildfire damages (Baylis and Boomhower 2026) have been shown to vary substantially within small geographic areas, partly reflecting differing levels of adaptation investment at the property level. The literature on flood and hurricane damages is further challenged by the fact that researchers often observe *predicted* flooding from a hydrological event model, as opposed to realized flooding on the ground.

Another strength of the dataset used for this paper is the ability to observe income and employment from individual tax returns. With the exceptions of Deryugina, Kawano, and Levitt (2018) and Groen, Kutzbach, and Polivka (2020), both of which study a single mega-disaster (Hurricane Katrina), we are not aware of any other papers that use income data from tax returns to understand the financial consequences of natural disasters.

We find that, on average, households affected by wildfires have higher income and are more likely to be white than the US population, reflecting the geography of wildfire risk. While the average income is relatively high, the population of wildfire-exposed incomes has a wide range of incomes, with 25% of occupants of destroyed homes having incomes below $42,000 per year.[3] Perhaps more strik-

2. See for example Gallagher and Hartley (2017), Deryugina, Kawano, and Levitt (2018), Billings, Gallagher, and Ricketts (2022), and Gallagher, Hartley, and Rohlin (2023).

3. All dollar values in the paper are in year 2022 dollars.

ingly, there is a clear income gap between occupants of destroyed and surviving homes. This structure vulnerability gap is consistent with evidence of differences in structure survival according to age of home and other variables (Baylis and Boomhower 2026; Plantinga, Walsh, and Wibbenmeyer 2022), and with disparities in ex ante wildfire risk mitigation (Anderson, Plantinga, and Wibbenmeyer 2023; Sølvsten, Whitlock, and Liao 2024; Reining et al. 2025).

Relative to households outside of the burned area, average income for wildfire victims falls by 10% in the two years following the wildfire and remains below the level of the comparison group until the fourth post-fire year. In total, a typical wildfire victim foregoes the equivalent of 30% of their pre-fire single-year adjusted gross income across the years following the event. Accounting for these income reductions increases the financial impact for a typical wildfire victim by about 50% of the uninsured property loss amount. Among occupants of destroyed homes, there is an immediate and persistent effect on migration. Up to four years after the incident, more than 10% of households are still filing their taxes from a different county.

Turning to effects on burned communities, we find that rebuilding proceeds slowly and unequally. On average, 50% of destroyed homes remain unoccupied four years after a wildfire. Incomes among occupants of rebuilt homes are higher than the pre-fire average among destroyed homes, and the share of occupants over age 65 is notably lower.

Our results for wildfire can be compared to earlier work on the household financial impacts of other types of natural disasters. The most closely related study to ours is Deryugina, Kawano, and Levitt (2018), which leverages tax filings to measure the effects of Hurricane Katrina. Relative to those estimates, one advantage of our data is the ability to directly observe the property damage experienced by each individual tax filer. Another differentiating factor is that our dataset includes the near-population of individuals suffering wildfire losses over two decades, as opposed to a single exceptional event. Other studies use consumer credit data to study financial distress in the wake of floods, hurricanes, or tornadoes (Gallagher

and Hartley 2017; Billings, Gallagher, and Ricketts 2022; Gallagher, Hartley, and Rohlin 2023; Collier et al. 2024; Kahn, Ouazad, and Yönder 2024).

The income reductions that we measure for wildfire victims are larger and more persistent than those caused by Hurricane Katrina.[4] One potential explanation for this difference may be that wildfire-damaged properties are usually a total loss and require ground-up reconstruction and complete replacement of household belongings, often accompanied by a period of extended temporary accommodation. Floods and wind storms impose a wider range of damages. The result that income effects differ between hurricanes and other disasters is consistent with findings in Roth Tran and Wilson (2025), who study the effects of presidentially-declared disasters on county-level average income. We also find that income losses for wildfire victims are concentrated among residents who choose to relocate out of the incident area. For Hurricane Katrina, the opposite prevails in the data: out-migrants in the wake of the disaster have higher post-incident earnings.

Our work also adds to a small literature measuring the economic effects of wildfires. All of the studies of which we are aware focus on credit market outcomes. Issler et al. (2024) use real estate data to study changes in the housing stock and mortgage pre-payment for homes inside of burned area perimeters. They do not observe individual financial outcomes and do not differentiate between destroyed and surviving homes. Biswas, Hossain, and Zink (2023) also examine post-wildfire mortgage outcomes for homes that faced wildfire. They find that mortgages for destroyed homes are more likely to become delinquent and to be pre-paid. Kahn, Ouazad, and Yönder (2024) similarly finds that foreclosures and pre-payment increase in zip codes that experience wildfires. An, Gabriel, and Tzur-Ilan (2024) find that low-income renters within burned areas in Texas (averaging together destroyed and surviving homes) demonstrated higher levels of financial distress (higher spending, indebtedness, and loan delinquencies). In comparison to these

4. As we discuss below, this comes with the caveat that the analyses we have implemented to date are not exactly comparable to the design in Deryugina, Kawano, and Levitt (2018) in terms of the choice of control group.

studies of credit outcomes, our study observes income, employment, and migration information from tax filings and is able to track outcomes for households that migrate away from the wildfire area. In a very different context of historical urban fire, Schwank (2024) follows victims of the 1906 San Francisco earthquake and fire across subsequent decadal censuses finding short run displacement and associated negative impacts on human capital formation and entrepreneurship.

Existing evidence on migration after wildfires suggests that experiencing a large wildfire leads to migration in the short-run. Winkler and Rouleau (2021) find that counties that experienced large wildfires had reduced in-migration and increased out-migration in the following year. McConnell et al. (2024) show that large wildfire events are associated with internal migration within the United States. Smaller events, particularly those that destroy few homes, lead to little migration. Hennighausen and James (2024) find that most residents who file change of address forms after the Camp Fire relocated within one hundred miles of their original homes.

A small body of evidence looks for racial and wealth disparities in exposure to wildfire risk. Davies et al. (2018) and Wibbenmeyer and Robertson (2022) examine the geographic coincidence of predicted wildfire hazard from a fire hazard model with race, income, and other variables measured at the aggregate level (e.g., Census tract). Anderson, Plantinga, and Wibbenmeyer (2023) and Sølvsten, Whitlock, and Liao (2024) show that fuel-reduction projects and FIREWISE participation are more common in affluent communities (holding local fire hazard constant). Reining et al. (2025) shows greater frequency of updating roofs in less disadvantaged Census tracts.

The paper proceeds as follows. Section 2 describes the construction of the dataset. Section 3 summarizes results related to wildfire hazard and vulnerability. Section 4 reports estimates of the causal effect of wildfire property loss on earnings, employment, and migration. Section 5 reports results for neighborhood-level changes and post-disaster gentrification. Section 6 discusses the results and Section 7 concludes.

2 Data

We construct a new individual-level panel dataset on wildfire property damages, occupant demographics, and post-incident economic outcomes. Sections 2.1 and 2.2 describe the input datasets and Section 2.3 describes construction of the merged dataset.

2.1 Wildfire Property Damage

Our data on address-level wildfire damages build on the dataset created Baylis and Boomhower (2026) and are described in detail in that paper. The dataset includes house-level damage outcomes for homes located inside more than 100 wildfire burned areas in five western U.S. states. The data represent more than 70% of all U.S. wildfire-destroyed homes during 2003–2022 and more than 85% of wildfire-destroyed homes in the included states (California, Arizona, Colorado, Oregon, and Washington). The data were assembled by requesting and harmonizing individual post-incident damage censuses conducted by county and state emergency response officials.

We also present auxiliary analyses of properties destroyed during the 2025 Los Angeles wildfires. These analyses draw on publicly-available damage provided by CAL FIRE.

2.2 Tax and Census Data

Individual-level demographic characteristics and economic outcomes come from the Environmental Impacts Frame (EIF), a dataset assembled for environmental social science research by researchers affiliated with the United States Census Bureau. The EIF draws on restricted-access microdata from the American Community Survey and from the universe of tax returns filed with the Internal Revenue Service. It includes individuals observed annually between 1999 and 2022. The EIF also identifies a household's home location in a given year. Location in the EIF

is usually determined by the location in the tax filing, unless a more recent address is available from another source, such as the ACS. The construction and contents of the EIF are described in more detail in Voorheis et al. (2023). When considering effects on earnings, we restrict this sample to individuals between 25 and 65 years of age. We use adjusted gross income as our primary income measure. This includes labor and self-employment income, transfer payments, and retirement withdrawals.

2.3 Construction of the Merged Dataset

We merge damaged homes in the wildfire data to addresses in the EIF data using a combination of geographic coordinates and address data. This combination allows us to link the data to the Master Address File Auxiliary Reference File, an internal dataset within Census that identifies individual-address pairs for a given year. We then link the individual identifiers, which are known as a Protected Identification Key or PIK, to obtain the income and demographic data. As mentioned above, this process is described in more detail in Voorheis et al. (2023).

Our merged dataset is limited to occupants of single family homes. This is the group for which we are able to merge the damage data to the Master Address File Auxiliary Reference File with the greatest confidence. Single family homes comprise 88% of destroyed residences in the wildfire damage assessment data.

The main analysis dataset includes four categories of homes for each incident.

1. *Destroyed*: Individuals whose primary residence was inside the wildfire perimeter and was destroyed.
2. *Survived*: Individuals whose primary residence was inside the wildfire perimeter and was not destroyed.
3. *Adjacent*: Individuals whose primary residence in the year of the fire was between 0 km and 25 km *outside* of the wildfire perimeter. To construct this group, we draw from individuals who are included in a 10% random sam-

ple of the pooled American Community Surveys (ACS) from 2005–2022.[5] In auxiliary analyses, we divide the adjacent group into 0-10 km and 11-25 km from the fire.

4. *Pure Control*. random sample of individuals whose primary residence in the year of the fire was in an unaffected commuting zone in the same state as the fire.

As an example of the resulting data for a single wildfire, Fig. 1 shows destroyed, surviving, and adjacent homes for the 2020 Glass Fire near Santa Rose, California.[6]

3 The Distribution of Wildfire Hazard and Vulnerability

This section describes the socio-economic characteristics of wildfire-exposed Americans. Section 3.1.1 compares destroyed and surviving homes to the US population and to nearby unaffected homes. Section 3.1.2 compares the occupants of destroyed vs. surviving homes, conditional on exposure to a wildfire event. Section 3.2 presents similar comparisons based only on within-event variation. Section **??** presents auxiliary analysis of the 2025 Los Angeles fires, which are not included in the main analysis dataset due to their recency.

3.1 Cross-Sectional Evidence

3.1.1 Wildfire Hazard

Table 1 describes pre-fire characteristics of the various samples. We begin by comparing occupants of homes located in burned areas (Column (4)) to the U.S. pop-

5. Each annual ACS is a random 1% sample from the full population of housing units, making the sample we use here approximately a 2% random sample from the full population of households in these areas.

6. For plotting representative adjacent home locations, we draw a 2% random sample of single family homes from ATTOM real estate data. The resulting sample in the plot is for illustration and does not exactly match the analysis sample.

ulation and to nearby unburned areas (Columns (2) and (3)). Occupants of affected homes have a pre-fire adjusted gross income of $183,000, notably higher than nationwide average of $119,00 for single family homes and $118,000 for adjacent unaffected communities. The same patterns exist when considering only wage earnings, although the difference between affected and adjacent unaffected is smaller.

The racial and ethnic composition of wildfire-affected households also differs from the U.S. population and from adjacent unaffected areas. Eighty percent of wildfire-affected individuals are white, compared to 68% for U.S. single family homes and 49% in adjacent unaffected areas.

3.1.2 Structure Vulnerability

Columns (5) and (6) separate the results for the Affected group into occupants of homes that were destroyed vs. not destroyed by the wildfire. There is a clear difference in pre-fire income across the two groups, which have pre-AGI of $129,000 and $204,000. The same gap is present when considering wage earnings only. Differences in other pre-fire characteristics between occupants of destroyed and surviving homes are smaller and mostly not statistically significant.

Going beyond the mean values in Table 1, Figure 2 summarizes the empirical distributions of pre-fire income for destroyed and surviving homes. The solid orange line represents occupants of destroyed homes. There is substantial variance of pre-fire AGI among these households. The lowest 25% are below $42,060, while the higest 25% are above $148,300. The highest-earning 5% of fire victims had pre-fire AGI above $835,400. The dashed line represents occupants of surviving homes. The income gap between the destroyed and surviving groups is present throughout the distribution. The median pre-fire income is $82,000 for occupants of destroyed homes vs. $115,000 for surviving, a 40% difference. The wealthiest 5% of surviving-home households have AGI over $1,500,000.

3.2 Within-Fire Comparisons

Table 2 explores the degree to which the measured vulnerability gaps in income reflect within-fire variation in survival vs. correlation between destructiveness and average income across different fires. To ensure empirically-meaningful sample size in the within-fire comparisons, we limit the sample to the 20 largest fires by number of homes affected. We also limit the sample to homes located inside the burned area, so that we focus only on differences between destroyed and surviving homes. Column 1 reports the estimate and standard error from a regression of pre-fire AGI on an indicator for destroyed. This overall vulnerability gap corresponds closely to the difference in mean AGI between destroyed and surviving homes reported in Table 1, which uses all incidents in the data. The estimates in Column 2 come from a regression that also includes incident fixed effects. Thus, this estimate reflects the average gap in income *within* a given wildfire incident. This within-fire vulnerability gap is accounts for about two-thirds of the overall vulnerability gap. Finally, Column 3 includes granular incident-by-street fixed effects and additional control variables such as lot size. These fine-grained controls for local fire intensity and individual property characteristics shrink the gap somewhat, but there remains a roughly $20,000 gap in income between destroyed and surviving homes.

3.3 The 2025 Los Angeles Wildfires

Table 3 presents auxiliary analysis of the January 2025 Los Angeles wildfires, which are not included in the main analysis dataset because their recency precludes detailed analysis of post-fire outcomes. The Eaton Fire near Pasadena affected individuals with a moderately higher AGI than the Los Angeles county average. The population affected by the Palisades Fire near Pacific Palisades was highly affluent on average. In both cases, we see notable gaps in income between occupants of destroyed and surviving homes.

4 The Effects of Wildfire Property Loss on Households

This section describes the effects of home loss on individuals' economic outcomes. Section 4.1 grounds the analysis in a simple model of household economics. Section 4.2 documents the local projections approach we use for estimation and Section 4.3 reports on the findings for migration and wage outcomes.

4.1 The Household Economics of Disaster Loss

This section develops a simple framework to put our empirical analysis in appropriate economic context. Consider a household that maximizes utility from consumption c and leisure $1 - l$ across two periods 1 and 2.

$$\max_{c_1,c_2,l_1,l_2} u_1(c_1, l_1, D\alpha) + u_2(c_2, l_2) \tag{1}$$

$D \in \{0, 1\}$ is a binary random variable representing whether or not a disaster occurs in period 1. α represents direct non-monetary disutility of the disaster event (e.g., pyschological distress). Wealth includes exogenously-given initial assets m, monetary property damages $D \times L$, insurance payments $D \times I$ and per-period labor income $y_1(l_1; D)$ and $y_2(l_2; D)$. Income depends on hours worked and whether or not the disaster occurred (capturing, e.g., the effect of the disaster on available wages, ability to work, and/or commuting costs). The household borrows or saves at interest rate r. The budget constraint is,

$$c_1 + \frac{1}{1+r}c_2 = m - D(I - L) + y_1(l_1; D) + \frac{1}{1+r}y_2(l_2; D) \tag{2}$$

Even in this stylized model, empirical assessment of the utility effects of a disaster is challenging. Consider, for example, the equivalent variation (EV) – that is, the income reduction in the no-disaster state that would yield the level of utility in the disaster state. Calculating the EV requires knowledge of the household labor supply curve, the shape of consumption utility, the asset endowment, non-monetary disaster disutility, and other parameters. Such a calculation is beyond the grasp

of this study and for the most part beyond the disaster literature more broadly.

We focus instead on a more modest, but also interesting, object: the effect of the disaster on the present value of lifetime income and assets. This quantity speaks directly to the household's lifetime consumption of market goods. To simplify notation, let y'_t and y^0_t represent realized income in period t with and without the disaster. The difference in the present value of lifetime income between the disaster and no-disaster states is

$$\underbrace{-L + I}_{\substack{\text{property damages} \\ \text{net of insurance}}} + \underbrace{y'_1 - y^o_1}_{\substack{\text{short-run} \\ \text{income change}}} + \frac{1}{1+r} \underbrace{(y'_2 - y^o_2)}_{\substack{\text{long-run} \\ \text{income change}}} \tag{3}$$

The disaster affects the budget through three channels. First, it reduces assets by the cost of property damages net of insurance. Second, it may change period 1 income by changing the returns to work and/or labor supply. Third, the disaster may also change period 2 income if it has long-run effects on returns to work or labor supply.

Our data allow us to measure income changes up to four years after wildfire events, illuminating the short-run effect $y'_1 - y^o_1$ and, to some extent, the longer-run effect $y'_2 - y^o_2$. We do not observe L, the cost of property damages, or I, insurance payments. However, a repeated finding in case studies of wildfires is that $L \geq I$, such that the net property damages from the event leave households worse off, even before considering the pyschological and other non-monetary costs of property loss.[7] Another advantage of the AGI data that we use is that they include withdrawals from retirement accounts and many forms of government transfers, including unemployment insurance. Thus, in this model, measured reductions in income due to the disaster represent a plausible lower bound on the total negative effect of the

7. Cookson, Gallagher, and Mulder (2025) use policy-level data to show that 74% of destroyed homes in the devastating 2021 Marshall fire in Colorado had insurance policy limits below reconstruction cost. Klein (2018, 2023) report more broadly on the prevalence of and reasons for low coverage limits among U.S. homeowners.

disaster on household finances.

4.2 Estimation

We estimate the impulse response of migration and income to wildfire occurrence using a panel local projections model following Jordà (2005) and Jorda and Taylor (2025). As described by Dube et al. (2023), an advantage of the local projections model is that it naturally accommodates recent insights about two-way fixed effects estimators with varied treatment timing (e.g., Callaway and Sant'Anna 2021; De Chaisemartin and d'Haultfoeuille 2020). The model considers how a fire in year t affects outcomes in year $t + h$, where h is between -4 and 4. Our preferred specification includes controls X_i as well as fire f-by-year t fixed effects and takes the form:

$$y_{i,t+h} = \beta_h^D 1[\text{Destroyed}]_i + \beta_h^S 1[\text{Survived}]_i + X_i + \phi_f \times \phi_t + \varepsilon_{i,t+h} \tag{4}$$

We run these as separate regressions for each value of h (excluding $h = 0$ for migration outcomes and $h = -1$ for income outcomes). The estimates we report are the β^D and β^S for each value of h. All the β_h capture changes in the outcomes relative to the Adjacent Unaffected comparison group individuals for each fire. We include fire-by-calendar year fixed effects as a baseline, however results are robust to other plausible fixed effects specifications.

Identification in this setting is produced by the spatial and temporal unpredictability of wildfire occurrence. By focusing on individuals living relatively near a wildfire perimeter we ensure good comparability across non-wildfire determinants of the economic outcomes we estimate. In the event-by-year fixed effects specification, the fixed effects absorb arbitrary trends in economic outcomes at the location of each fire, with the β_h coeffecients capturing differential outcomes for the destroyed and survived groups relative to the outside-the-fire comparison group. The β_h estimates for $h < 0$ provide tests of pre-trends in these outcomes and support the identification assumption that the relative outcomes did not change at the

exact time of the fire for reasons unrelated to the fire itself. The addition of direct controls X_i in some specifications helps ensure against any remaining confounding variation, though we don't view it as essential to the identification strategy.

Direct comparisons between effects for Destroyed and Surviving groups require slightly more consideration, given the pre-fire income differences for these groups in Table 1 and prior work that shows that structure survival is determined in part by structure characteristics, spatial arrangement in relation to other structures, and defensible space (see, e.g., Syphard et al. 2012; Plantinga, Walsh, and Wibbenmeyer 2022; Baylis and Boomhower 2026). In auxiliary analyses and robustness checks, we scrutinize pre-fire trends in the various treatment and comparison groups. We also confirm the robustness of the results to controlling for pre-fire income, individual fixed effects, and other specifications.

Our preferred specification with event-by-year fixed effects measures the difference in outcomes between individuals who lived inside or just outside the wildfire perimeter at the time of the fire. By design, this specification differences out trending factors that affect both adjacent and exposed homes. To the extent that the fires in our sample affected wages or other labor market dynamics in both the exposed and adjacent areas, those wage changes will not be reflected in estimates from this specification. We thus conduct auxiliary analyses using the "pure control" comparison group of homes in other labor markets to investigate these possible wage effects. We return to this point in Section 6.

4.3 Results

4.3.1 Income

Fig. 3 reports the average effect on the log of Adjusted Gross Income, pooling together occupants of destroyed and surviving homes. This specification mimics what would have been possible without the individual-level damage data. The estimates are near zero in all pre-fire years, implying that there were not differential trends in income among the exposed populations and the adjacent comparison

group in advance of the wildfire. In year 0, the year of the wildfire, there is a small decrease in income. This small decrease is consistent with the fact that most wildfires in the dataset occur late in the calendar year. In the two years following the wildfire, the exposed group sees a roughly 4 percentage point decrease in income on average. The effects persist in a more modest way through the third post-fire year before returning to zero in year four.

Fig. 4 estimates income changes separately for occupants of destroyed and surviving homes. Panel A shows that the average effects for income in the previous figure are almost entirely explained by large income reductions among individuals who suffered a property loss. The income reductions for this group persist for three years, peaking at 11% in the second year and returning to zero in the fourth year. The occupants of surviving homes fare much better in terms of post-fire income, with little departure from pre-fire income. Panel B shows that results are similar when we consider only wage earnings. We use the inverse hyperbolic sine of wages in Panel B due to zero values in the wage data.

The effects in Figure 4 are the difference between occupants of properties in the burned area and properties immediately outside. Particularly destructive wildfires could also have economic effects that extend beyond the fire perimeter. Figure 5 shows effects on earnings relative to various comparison groups, including the "pure control" group in commuting zones unaffected by the fire. The results are highly similar, implying limited local wage effects. We return to this point in the Discussion.

4.3.2 Employment and Assets

Figure 6 shows effects for other household economic outcomes. There is little measurable impact on the probability of any employment and on the likelihood of job change. There are large immediate impacts on home ownership for occupants of destroyed homes, implying many sales immediately post-fire with eventual return to ownership over several years. Occupants of destroyed homes also draw down tax-deferred retirement savings, as evidenced by data from IRS Form 1099-R. No-

tably, typical penalties for these withdrawals are waived by law in the wake of disaster events.

4.3.3 Migration

We define migration as relocating to a different county, using the address of the tax return as our measure of household location. We note that these estimates likely under-report migration since not all moving families change their addresses for tax reporting purposes. Fig. 7 reports results. The outcome variable in Panel A is an indicator for whether the household lives in the same county as in the year of the fire. There are notable pre-fire differences in mobility between the two exposed groups and the adjacent unaffected homes that make up the comparison group. During the four years prior to the event, the survived and destroyed groups are about 5 percentage points more likely to have been in a county other than the one where the event occurred. However, there is no difference in pre-period mobility trends between the destroyed and surviving groups. After the wildfire, the differential share of households migrating spikes to about 12% for the destroyed group. Four years later, most of these households have still not returned. Panel B shows that cross-state migration is much less common, suggesting that most of the post-fire movement that we observe is relatively local.

4.3.4 Heterogeneity in income effects

Figure 8 describes outcomes conditional on choices made by destroyed home occupants. Panel A shows that income reductions are larger among wildfire victims who owned their home prior to the event. Panel B shows that income reductions are larger among individuals who choose to relocate away following the event.

4.4 Robustness of the Results

We implement a range of robustness tests to confirm the validity of the main results. These include balanced panel specifications that use only events with four

years of pre- and post-fire data; other sets of fixed effects; a "donut" specification that compares exposed homes to homes 10-25 km outside the wildfire perimeter; and regressions that focus on wage earnings instead of AGI.

5 Neighborhood Changes

This section shifts the unit of analysis to addresses within the burned area perimeter, and considers how the composition of neighborhoods changes before and after a damaging wildfire.

In this draft, we present time-varying summary means. We intend to update these analyses using local projections in ongoing work.

Figure 9 shows that rebuilding is quite slow on average. Almost all destroyed and surviving addresses were claimed as a primary address on someone's tax filing in the years prior to the fire. Surviving addresses continue to be occupied post-fire, but destroyed addresses see a roughly 50% decrease in the occupancy rate that persists for four years after the event.

Figure 10 shows that the composition of individuals living in fire-destroyed addresses changes notably after the fire. This is true for both income and the share of the population over age 65. These effects may reflect changing property ownership, faster return to occupancy for higher-income pre-fire owners, or both. In ongoing work we intend to isolate these possible explanations.

6 Discussion

6.1 Who is exposed to wildfire risk and who loses their home?

Our results offer new insight into the demographics of wildfire risk in the United States. The data show that the population most exposed to this increasingly-severe peril differs from the groups most exposed to other weather disasters. Table 4

summarizes mean pre-event incomes reported in studies of other types of natural disasters, adjusted to year 2022 dollars. One interesting benchmark is the national sample of Federal Disaster Loan applicants in Collier and Ellis (2024). That dataset includes victims of many different types of disasters, though the bulk are severe storm and hurricane events. The average pre-event income among that group is $84,275, compared to $145,679 for wildfire victims.

To some extent, these differences reflect differences in nominal wages across regions of the country. Hurricane and flood risk are concentrated in the Southeast, while many damaging wildfires occur in California (which is at the intersection of population density and physical factors that create wildfire risk). It is also important to note that while average incomes of fire-exposed populations are relatively high, there is a wide range within that group as shown in Figure 2. Twenty-five percent of wildfire victims have incomes below $42,000.

The address-level damage data allow us to differentiate outcomes for occupants of destroyed vs. surviving homes. The clear income difference here is suggestive of a " structure vulnerability gap". Much of this gap is explained by within-incident correlations between income and property loss. The possibility of such a gap has been hinted at in earlier work that shows differential wildfire damage outcomes by building vintage and other factors (Baylis and Boomhower 2026; Syphard et al. 2012). It is also consistent with work showing greater public investment in fire prevention in affluent areas (Plantinga, Walsh, and Wibbenmeyer 2022). The results here reinforce the value of working with individual-level damage data. They also underscore the importance of identifying effective vulnerability-reducing interventions. Finally, the systemic differences in property loss that we document here make it even more important to ensure that property insurance markets function as well as possible.

6.2 Income reductions for wildfire victims

The data show significant, persistent reductions in income for individuals who lose their home in a wildfire. For a homeowner with the mean AGI in our destroyed homes sample, the income reductions across years in Panel A of Figure 4 imply total earnings losses of about $38,000. These earnings losses add meaningfully to the total financial hit taken by wildfire victims. Equation 3 shows how the total effect of the wildfire on lifetime consumption depends on income changes and uninsured property damages. Cookson, Gallagher, and Mulder (2025) use rich data from a large Colorado wildfire and find that insurance was adequate to cover 88% of rebuilding costs for the average fire victim. Applying that ratio to the average reconstruction cost for a California home in wildfire hazard areas of $600,000 from Boomhower et al. (2024) yields an estimate of typical uninsured property damages of $72,000. The income reductions that we measure in this study add roughly 50% to that loss number for the typical wildfire victim.

The substantial negative effects on income for wildfires are perhaps even more interesting given that most homeowners have at least partial insurance coverage. Unlike flood damage, wildfire is covered by the standard homeowners insurance policy required by virtually all mortgage lenders. One factor driving the income losses that we measure may be that wildfire-damaged homes are typically completely destroyed and require ground-up reconstruction. Fire victims also lose essentially all of their belongings inside the home. Floods and hurricanes impose a wider range of damages, including some smaller losses with accompanying shorter repair times. The median total loss amount (insured and uninsured damages) among FDL applicants in Collier and Ellis (2024) is $51,000, which implies a more limited extent of damage for the typical storm or flood victim.

6.3 Local labor market impacts

The main analyses focus on narrow comparisons in- and outside of the wildfire burned area. This specification follows the real estate literature on mortgage and

home price outcomes after wildfires (McCoy and Walsh 2018; Issler et al. 2024; Biswas, Hossain, and Zink 2023; Kahn, Ouazad, and Yönder 2024) as well as papers in the literature on financial impacts of other disasters Billings, Gallagher, and Ricketts (2022), Gallagher and Hartley (2017), and Gallagher, Hartley, and Rohlin (2023). A separate literature on the financial consequences of mega-disasters – in particular, Hurricane Katrina – emphasizes comparisons between affected individuals and individuals in matched "control" cities or counties located far from the disaster area. These comparisons are motivated by the possibility that large disasters may affect local wages (for example, by increasing demand for construction labor) and that such effects are part of the overall effect of interest. In particular, (Deryugina, Kawano, and Levitt 2018; Groen, Kutzbach, and Polivka 2020) attribute the wage gains among Hurricane Katrina victims to increased labor demand and decreased labor supply in the affected area.

We run similar "pure control" specifications for wildfire victims to investigate whether such effects are present in our setting. There is no evidence of important local labor market effects from wildfires along the lines of those that followed Hurricane Katrina. Katrina was the costliest natural disaster in U.S. history, causing over $200 billion of property damage over a wide geographic area, and was followed the same year by another $40+ billion of damage from Hurricanes Rita and Wilma in nearby areas. These losses are an order of magnitude larger than the costliest disaster in our incomes analysis, the 2018 Camp Fire. The Camp Fire caused $18 billion of property damage.[8] Most wildfire incidents are substantially smaller.[9]

To the extent that local labor market effects do occur for major wildfire events, specifications using nearby and far away control groups are both useful. The far-away

8. Damages from the 2025 Palisades and Eaton Fires in Los Angeles are currently estimated be about $40 billion. As victims of those fires file taxes in coming years, we will be able to update our estimates to reflect their experiences.

9. Best practices for protecting confidentiality prevent us from reporting the counts of individuals in each wildfire in our dataset, but 50% of the household observations in our matched dataset come from fires in years other than 2018.

controls speak to the importance of local labor market effects, while the adjacent-to-the-fire-perimeter controls identify the marginal income benefit of avoiding the destruction of a given home, holding occurrence of the disaster constant. This second parameter is relevant for the design and evaluation of policies that aim to encourage or subsidize home hardening and defensible space by individual property owners.

6.4 Income effects of wildfire vs Hurricane Katrina

It is interesting to compare the results in this study to the income effects experienced by households exposed to Hurricane Katrina in Deryugina, Kawano, and Levitt (2018). The closest analogous specification in our paper to the main result in Deryugina, Kawano, and Levitt (2018) is the specification in Figure 3 that pools destroyed and surviving homes. We observe immediate income drops that persist for three years post-fire before returning to trend. The magnitude and in fact even the sign of the overall effect differs for Hurricane Katrina. The income losses from Hurricane Katrina in 2005 and 2006 were roughly similar to the year one effect for wildfires in percentage terms. However, by 2007 – two years after the storm – average incomes had fully recovered from the storm and further increased in years three, four, and after to levels higher than would have occurred in the absence of Katrina. Studies of post-Katrina consumer credit outcomes similarly find relatively limited financial damage given the scale of the event (Gallagher and Hartley 2017).

Our results for migrants also differ from the Hurricane Katrina literature. For wildfires, moving away from the fire location is correlated with substantially *worse* income effects across the four year post-period. Four years after the fire, AGI for this group is still 10% below those in the unaffected comparison group. In contrast, Deryugina, Kawano, and Levitt (2018) finds that Katrina survivors who did not return to New Orleans ultimately fared better than those who did not. Groen, Kutzbach, and Polivka (2020) finds that incomes ultimately converged for Katrina migrants and non-migrants, but that migrants had worse outcomes in the short

run.

6.5 Neighborhood Change and Post-Disaster Gentrification

There is substantial public and policy interest in the possibility of "post-disaster gentrification" – a change in the composition of neighborhoods affected by natural disasters. We show evidence consistent with important changes specifically for properties destroyed by the disaster. In ongoing work we will separate these effects into in-migration vs. differential speed in rebuilding for high-income pre-fire residents.

7 Conclusion

High-quality evidence on the economic burden of natural disasters is essential for designing policies to address growing extreme weather risks. We contribute new evidence on the distribution of wildfire hazard and vulnerability, as well as the post-incident effects of damaging wildfires on those who experience them. We analyze individual-level data on damages and economic outcomes for over 100 wildfire events representing about 70% of all wildfire-affected homes between 2003 and 2022.

We find that homes affected by wildfires largely reflect the overall geography of wildfire risk, which is concentrated in particular areas of the western United States. Wildfire victims are wealthier on average than victims of other natural disasters, in part reflecting nominal wage differences between wildfire- and hurricane-exposed areas. There is a wide range of pre-fire income levels for wildfire victims, with 25% of incomes below $42,000 and 5% of incomes above $835,400.

We also find a clear difference in pre-fire income between the occupants of surviving and destroyed homes inside of wildfire burned areas. The existence of such a gap in loss probability conditional on experiencing a wildfire reinforces the value of using individual-level damage data instead of neighborhood-level proxies to

understand economic effects of disaster loss. It also raises questions about how to successfully target risk mitigation initiatives towards all households in the exposed area.

The wildfire event causes substantial earnings losses, with income losses concentrated among households who suffer a total loss of the property. On average, the decrease in earnings persists for three years following the fire and returns to the level in the comparison group in the fourth. Adding these income reductions across years, the average wildfire victim foregoes an amount totaling 30% of their pre-fire adjusted gross income, or $38,000.

About 10% of individuals living in destroyed homes move to another county following the wildfire, and most have still not returned after 4 years. Our comparison of movers and stayers suggests that those who move suffer larger economic losses than those who stay, a reversal of the effects observed for Hurricane Katrina.

We also measure important neighborhood-level effects in burned communities. Four year after a wildfire, 50% of burned homes remain unoccupied and the average income for occupants of rebuilt homes is substantially above the pre-fire average.

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Table 1: Wildfire Victims vs. the U.S. Population

	Reference Populations			Wildfire-Affected Population		
	(1)	(2)	(3)	(4)	(5)	(6)
	U.S. Population	U.S. Single Family Homes	Adjacent Unaffected	All Affected	Destroyed	Survived
Income						
Pre-fire AGI	106,400	119,300	117,600	183,235	129,000	204,400
	(356)	(433)	(320)	(-)	(2,340)	(5,661)
Pre-fire Wages	49,260	53,200	76,410	97,109	71,250	107,200
	(95)	(121)	(298)	(-)	(1,155)	(3,125)
Race and Ethnicity						
Share White	62	68	49	80	84	78
	(0.024)	(0.026)	(0.042)	(-)	(0.24)	(0.17)
Share Hispanic	17	15	27	8.6	8.3	8.7
	(0.018)	(0.02)	(0.038)	(-)	(0.18)	(0.11)
Share Asian	5.3	4.8	13	6.2	2.9	7.4
	(0.011)	(0.012)	(0.029)	(-)	(0.11)	(0.11)
Share Other	3.4	3	6.6	3.9	3.2	4.1
	(0.0088)	(0.0096)	(0.021)	(-)	(0.11)	(0.081)
Share Black	12	9.2	3.3	0.97	0.6	1.1
	(0.016)	(0.016)	(0.015)	(-)	(0.05)	(0.043)
Share AIAN	0.91	0.88	0.56	0.92	1.4	0.74
	(0.0046)	(0.0053)	(0.0063)	(-)	(0.076)	(0.035)
Other Characteristics						
Age of Filer	40	41	48	52	53	52
	(0.011)	(0.013)	(0.015)	(-)	(0.12)	(0.073)
Share Male	49	49	49	49	49	49
	(0.024)	(0.028)	(0.042)	(-)	(0.33)	(0.2)
Observations						
Occupants			523,000	84,040	23,590	60,450
Homes				40,700	12,600	28,100

Notes: Dollar amounts are in year 2022 dollars. "U.S. Single Family Homes" reflects nationwide statistics for occupants of single family homes. "Adjacent Unaffected" includes occupants of homes located between 0 and 25 km outside the burn perimeter. "Affected" includes occupants of destroyed or surviving homes. Race and ethnicity shares are percentages and are coded as mutually exclusive categories (e.g., Share White Non-Hispanic). All observation counts are rounded for disclosure reasons.

Table 2: Within-event Vulnerability Gaps in Income

Cross Section	Fire Fixed Effects	Fire-by-Street Fixed Effects, Property Controls
-77,150***	-27,390***	-21,310***
(9,386)	(8,232)	(6,876)

Notes: Three different ways of calculating vulnerability gaps. All columns limit the sample to homes inside the burned area for the largest 20 incidents in the dataset. Column 1 reports the estimate and standard error from a regression of pre-fire AGI on an indicator for destroyed. Column 2 reports estimates from the same regression but including event fixed effects. Column 3 includes street-by-wildfire fixed effects.

Table 3: Income vs. Structure Loss, 2025 Los Angeles Fires

		Eaton		Palisades	
	Rest of LA	Destroyed	Survived	Destroyed	Survived
Mean AGI (1000)	120	141	222	870	962
SD	(0.4)	(4)	(4)	(5)	(6)

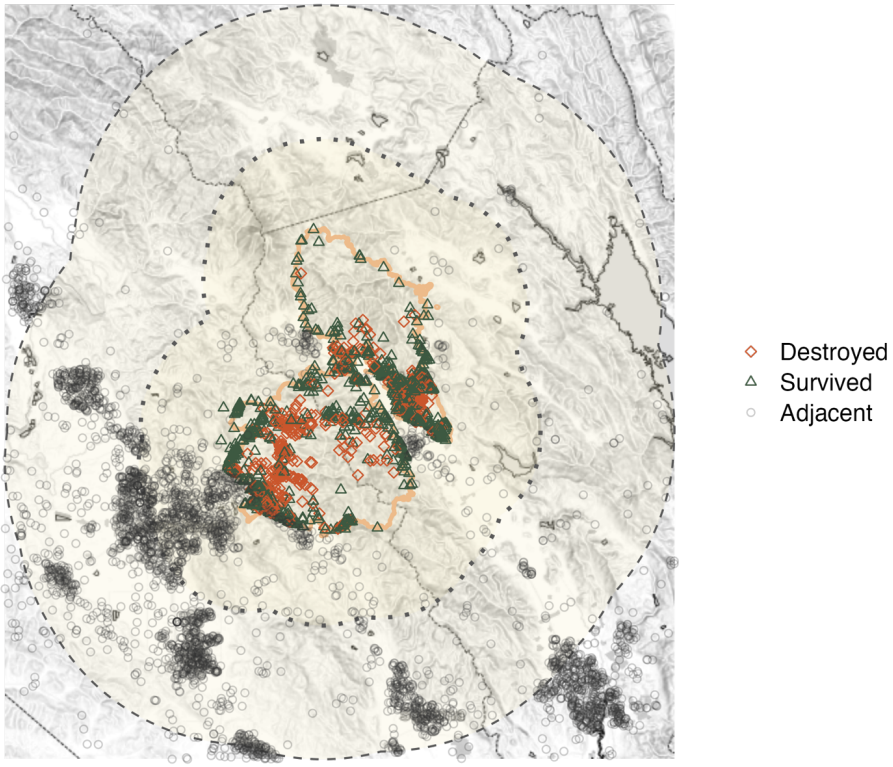
Notes: Means and standard deviations of adjusted gross income for occupants of the Eaton Fire perimeter, the Palisades Fire perimeter, and the rest of Los Angeles County. The 2025 Los Angeles fires are not reflected in other calculations in this paper due to their recency.

Table 4: Average Pre-Event Income for Wildfire-Affected Homes vs. Other Disasters

Study	Context	Mean Pre-Event Income ($2022)
Deryugina, Kawano, and Levitt (2018)	Hurricane Katrina	54,526
Collier and Ellis (2024)	Disaster Loan Applications	84,275
Billings, Gallagher, and Ricketts (2022)	Hurricane Harvey	89,632
This study	100+ wildfires	183,235

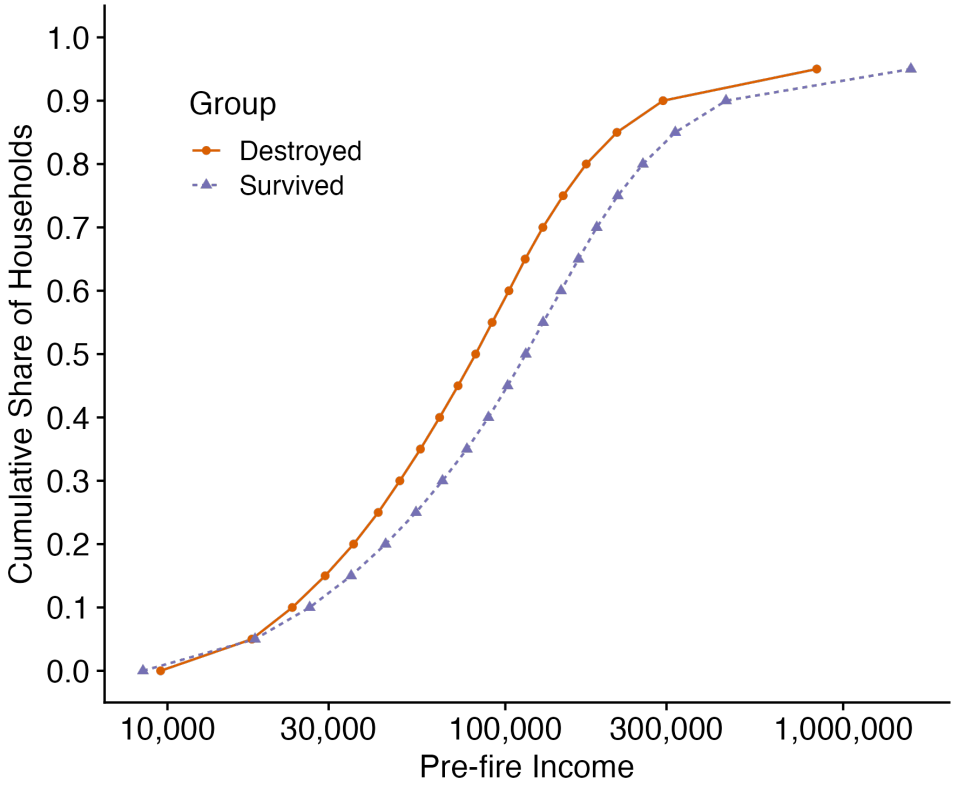
Notes: Values are reported mean incomes before the disaster event in each study adjusted to year 2022 dollars for consistency. Values in this study and Deryugina, Kawano, and Levitt (2018) are adjusted gross income.

Figure 1: Illustrating Destroyed, Survived, and Adjacent Homes



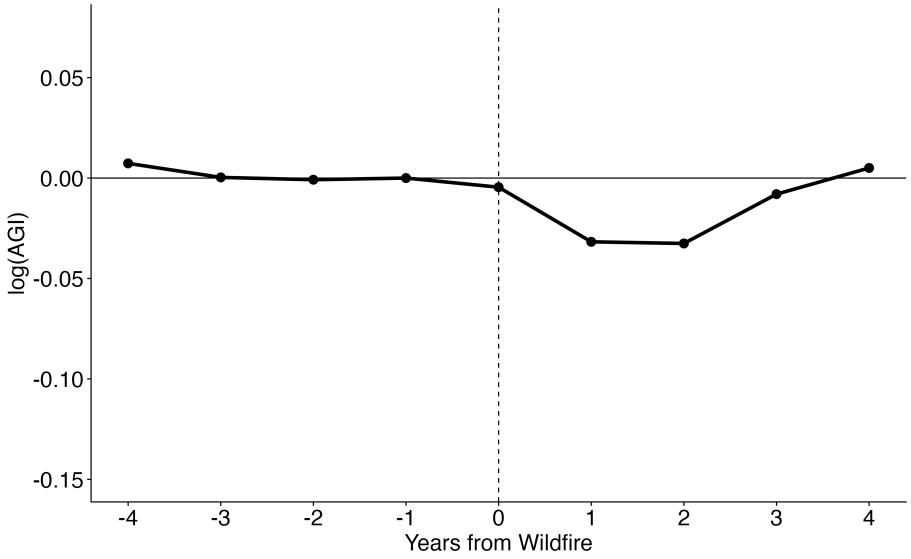
Colored markers indicate locations of destroyed and surviving homes for the 2020 Glass Fire in Northern California. The wildfire perimeter is in orange and the shaded buffer regions outside the fire perimeter represent 10 and 25 km adjacent areas, with gray circles representing a 2% random sample of homes in these adjacent areas.

Figure 2: Pre-fire Income Distributions for Occupants of Affected Homes



Notes: Figure reports the empirical cumulative distribution function of pre-fire AGI for occupants of destroyed and surviving homes (in 2022 dollars).

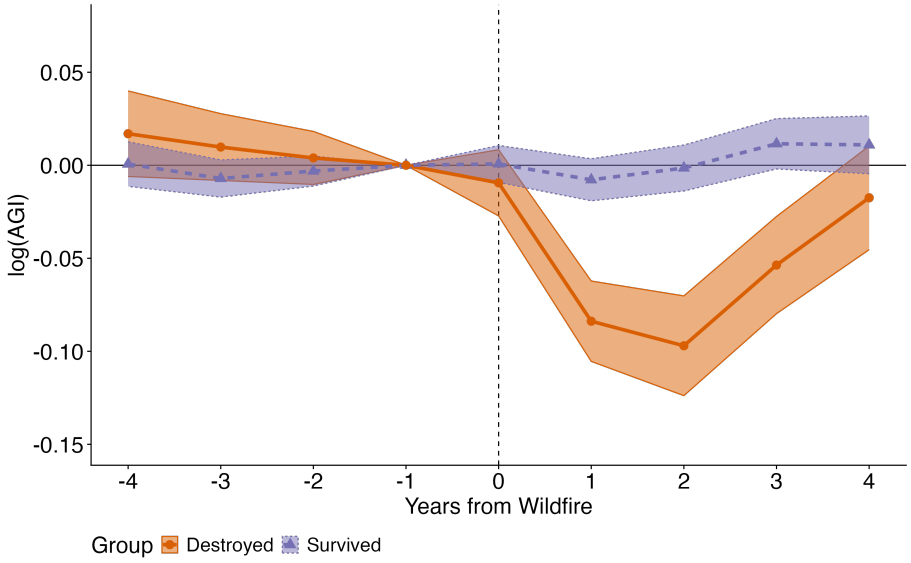
Figure 3: Effect of Wildfires on Incomes, Pooling Destroyed and Survived Homes



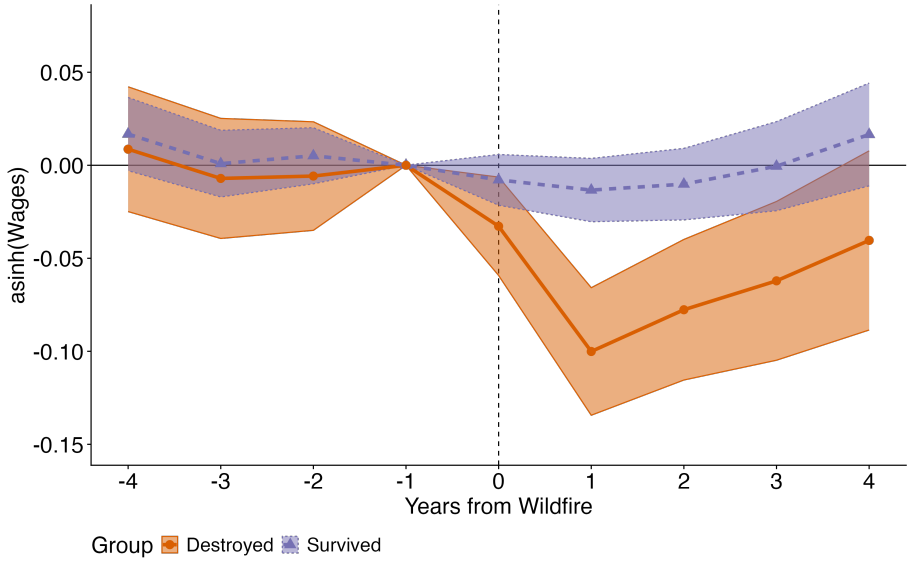
Notes: Figure reports local projection estimates of differential log adjusted gross income for occupants of destroyed homes relative to various comparison groups in years before and after the wildfire.

Figure 4: The Effect of Wildfires on Income by Damage

Panel A. Adjusted Gross Income

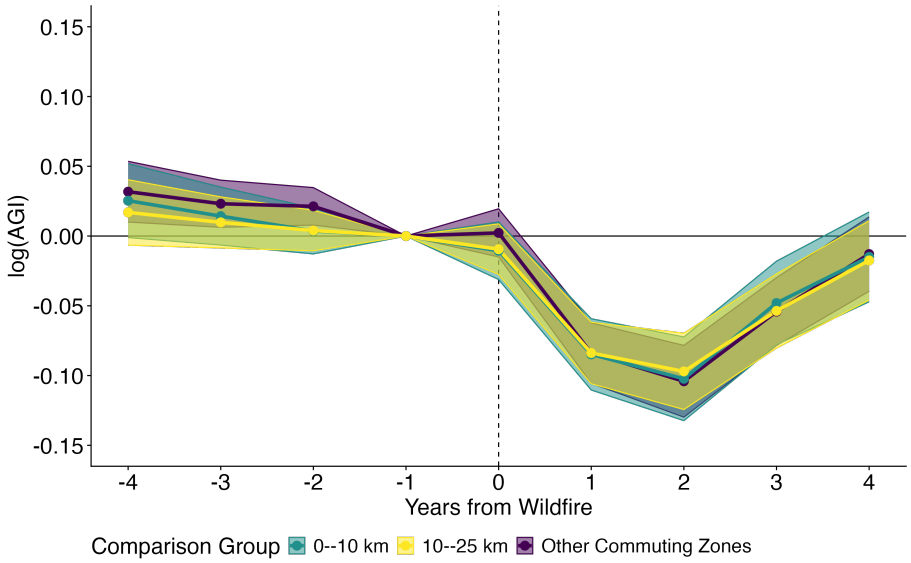


Panel B. Wages



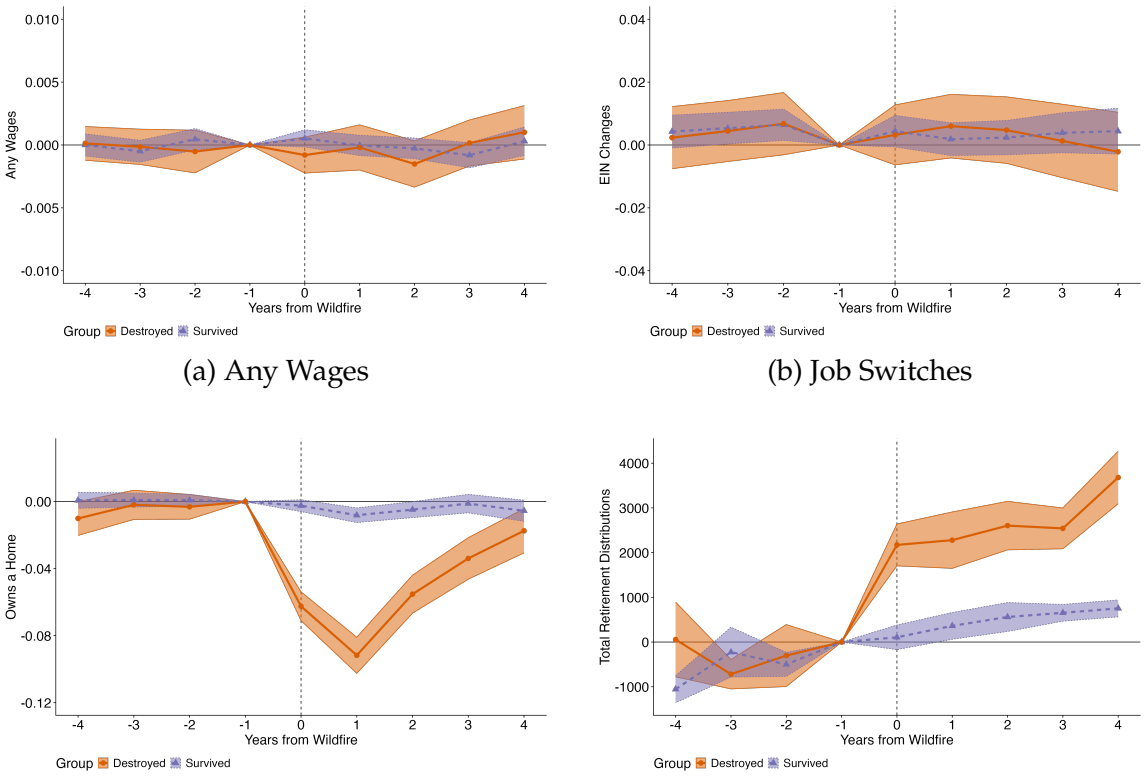
Notes: Panel A reports local projection estimates of differential log adjusted gross income for Destroyed and Survived groups relative to the Adjacent Unaffected group in years before and after the wildfire. Panel B reports similar local projection estimates for the inverse hyperbolic sine of wages.

Figure 5: Effect on Income Among Destroyed Home Occupants, Alternative Comparison Groups



Notes: Figure reports local projection estimates of differential log adjusted gross income for all affected homes relative to the Adjacent Unaffected group in years before and after the wildfire. Confidence intervals pending disclosure review.

Figure 6: Effects on Employment and Asset Ownership



(a) Any Wages

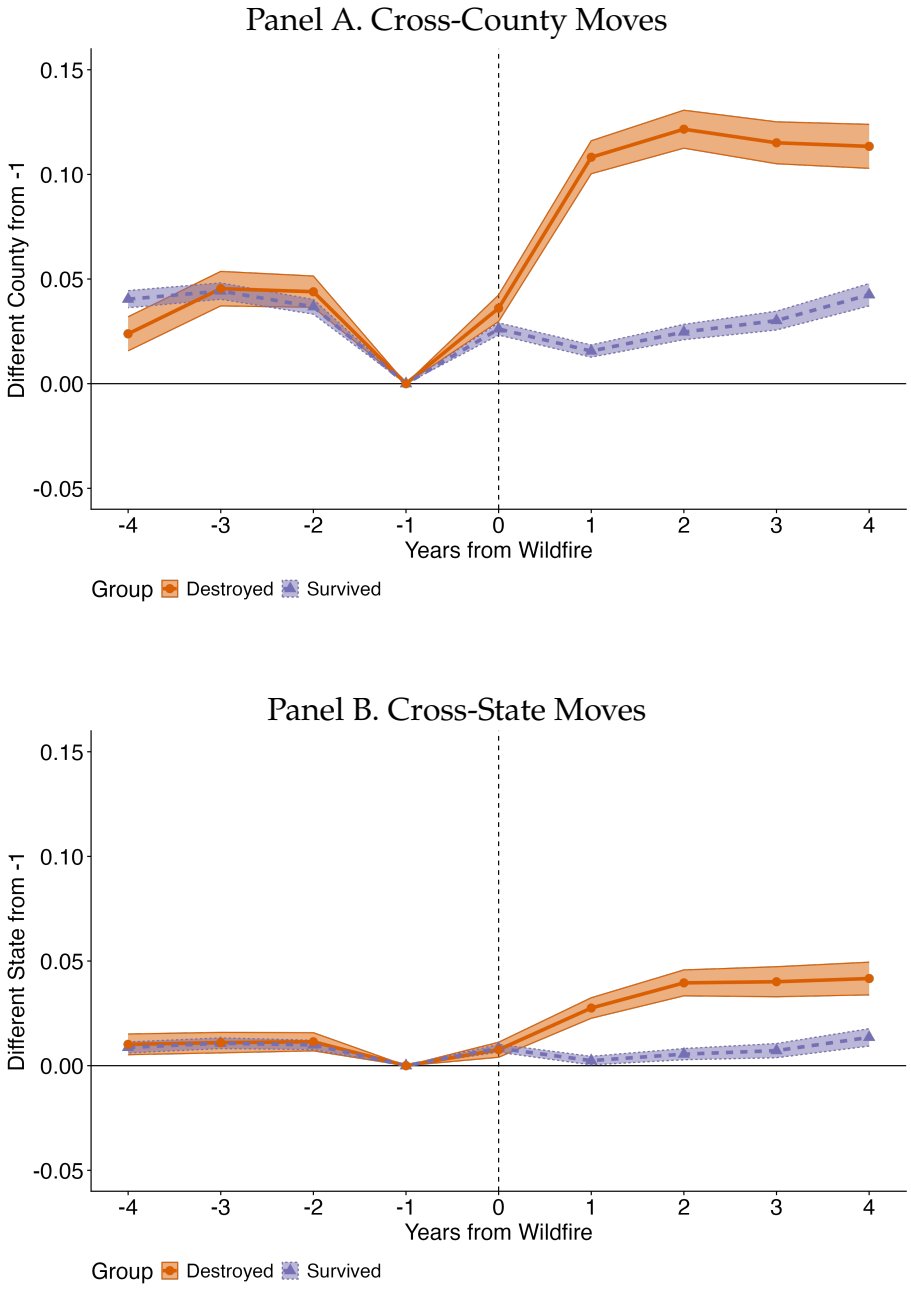
(b) Job Switches

(c) Home Ownership

(d) Retirement Account Withdrawals

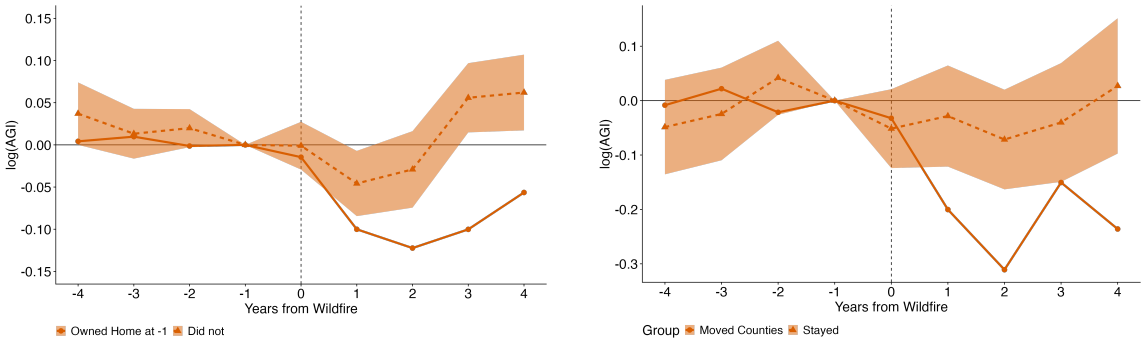
Notes: Panels (a) and (b) report local projection estimates for the probability of any wages and the probability of changing employers. Panels (c) and (d) report local projection estimates for the probability of owning a home and the amount withdrawn from tax-deferred retirement accounts.

Figure 7: Migration by Wildfire Victims



Notes: Figure reports local projection estimates of differential likelihood of living in the year -1 location for Destroyed and Survived groups relative to the Pure Control group in years before and after the wildfire. The household's location each year is defined as the address from which they file their tax return.

Figure 8: Heterogeneous effects on income

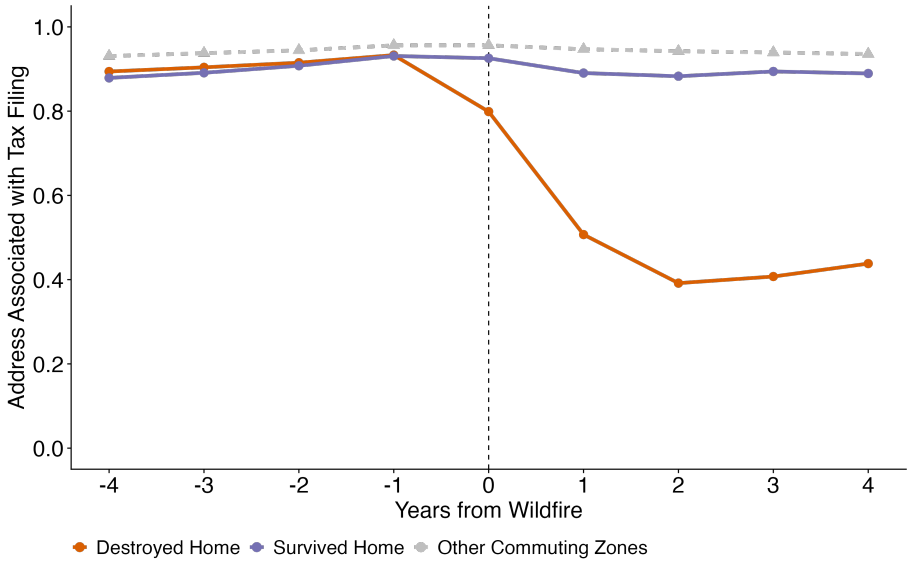


(a) By Pre-fire Home Ownership

(b) By Post-Fire Location Choice

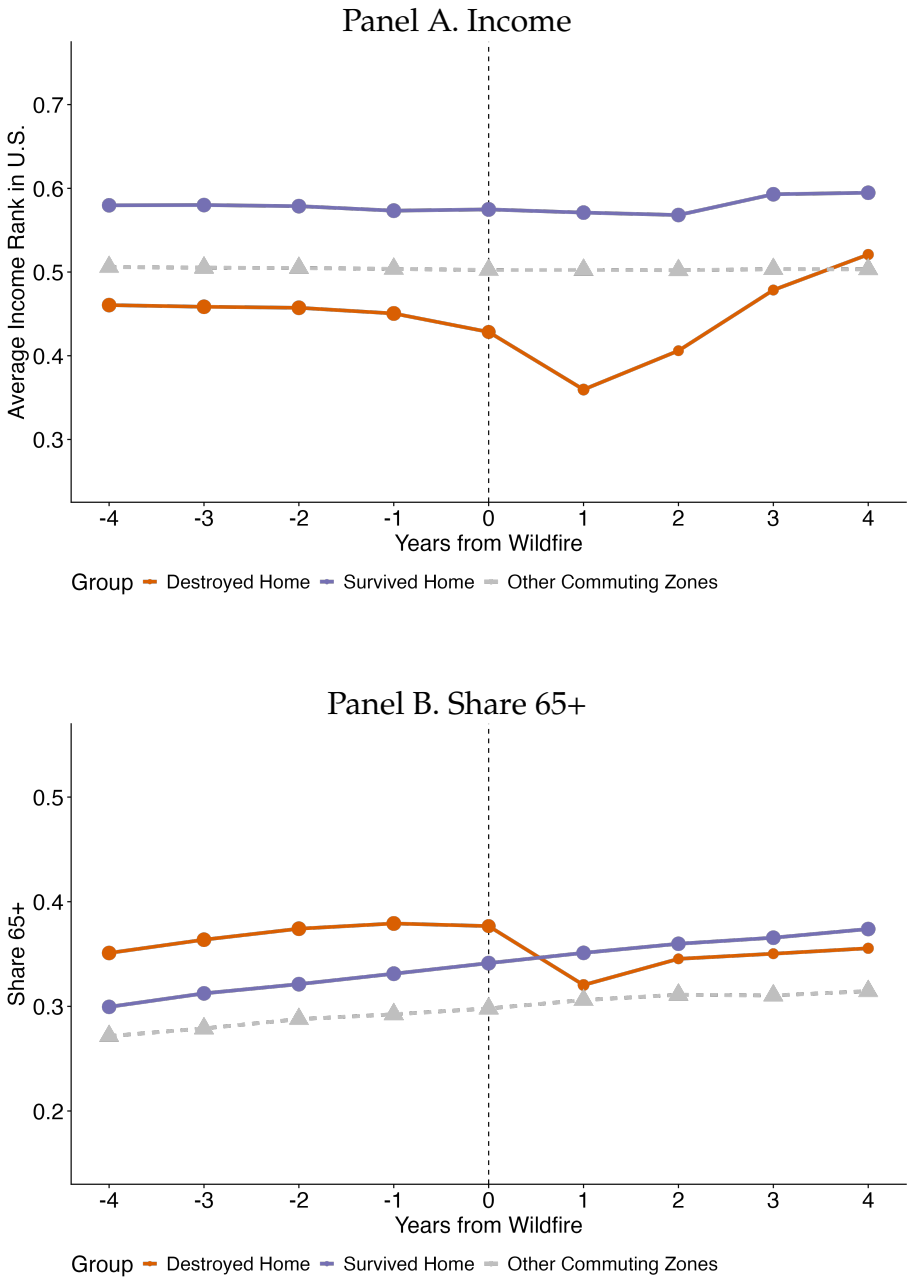
Notes: Panels (a) and (b) report local projection estimates for the probability of any wages and the probability of changing employers for different groups of destroyed home occupants. Confidence intervals pending disclosure review.

Figure 9: Share of Addresses Occupied Before and After Wildfire



Notes: Time-varying means of occupancy in years before and after the wildfire. Occupancy is defined as someone using the home as a primary address for tax filing.

Figure 10: Compositional Changes Among Occupied Addresses



Notes: Time-varying means of income and share 65+ for occupied addressed in years before and after the wildfire. Occupancy is defined as someone using the home as a primary address for tax filing.