The Fiscal Impacts of Wildfires on California Municipalities

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Abstract

This paper provides some of the first empirical estimates of the impact of natural disasters on the subcomponents of municipal budgets. We combine detailed municipal financial data from 1990-2015 with data on historical wildfire perimeters in California. We find that wildfires increase both revenues and expenditures. Sales taxes temporarily increase. Property taxes increase to a permanently higher level; this appears due to a California law that limits reassessments of property until time of sale. Wildfires also cause a long-term increase in local spending on community development and public safety. The overall impact of wildfires on municipal budgets is negative and substantial. That said, in comparison to the spending by state and federal governments on wildfire suppression and response, municipalities are surprisingly insulated from the costs of wildfires.

JEL classification: H71, H72, Q54, R51.

Keywords: wildfires, natural disaster policy, municipal budgets, Proposition 13.

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1 Introduction

Climate change is contributing to record-breaking extreme weather events and is altering the frequency, magnitude, extent, duration, and timing of many of these events around the world (Seneviratne et al., 2017). Wildfires are no exception, as seen in the recent devastating blazes in Australia in 2019-2020 and California in 2017, 2018, and 2020. In the U.S. west, wildfires are projected to increase in both frequency and intensity as the planet warms (Abatzoglou and Williams, 2016). Of all the western states, California has the greatest number of houses at risk of wildfire at close to 4.5 million (Martinuzzi et al., 2015).

Prior work has investigated the costs of natural disasters on household finance and also on aggregate measures of economic welfare for states and countries. There has been almost no empirical work, however, on how natural disasters affect local government budgets. Given the localized impacts of many natural disasters, this is a striking gap in understanding the full range of economic impacts from these events. In particular, maintaining fiscal soundness is crucial for local governments to consistently deliver the desired level of public services to residents. If a disaster leads to lower revenues or increased spending, this could entail greater borrowing and higher taxes down the road which may have negative welfare consequences for residents. Yet, these community-wide fiscal effects are not captured by previous estimates of the economic impacts of wildfires, most of which rely on comparing the values of exposed and unexposed properties in the same community.[1] As different fiscal conditions can create differences in quality of life and a municipality's long-term growth (Gyourko and Tracy, 1991), they should be considered in a complete examination of the economic impacts of wildfires.

An investigation of municipal fiscal impacts also allows us to better understand local governments' incentives to invest in risk-reduction measures. Prior work has shown that the costs and benefits of disaster risk mitigation are often disassociated, distorting decision-making. While local governments make many of the decisions that influence wildfire risk, such as the type and extent of building and land use, earlier work has shown

[1] For example, see Stetler et al. (2010), Mueller and Loomis (2014), McCoy and Walsh (2018), Garnache and Guilfoos (2019).

they bear little of the wildland firefighting costs, or the costs of repairing private property damaged by a wildfire (Baylis and Boomhower, 2019). This calls into question whether local governments have adequate incentives to invest in ex-ante risk reduction. No work, however, has yet investigated the fiscal impacts to municipalities directly.

In this paper, we provide the first estimates of the fiscal impacts of wildfires on municipal governments. We combine GIS data on historical wildfires in California with detailed, annual financial reports of California municipalities[2] spanning the years 1990 to 2015. The financial data, requested from the California State Controller's Office, contains a breakdown of municipal budget categories for both revenues and expenditures. The ability to track revenues across sources and expenditures across categories allows for a rich examination of the impact of wildfires on local finance. Moreover, we examine dynamic impacts for up to five year post-fire to understand the potential adjustments municipalities make to smooth any fiscal shock.

Since wildfires often burn undeveloped areas, which would have less impact on municipal budgets, we construct a population-weighted measure of wildfire exposure in a municipality and limit our attention to wildfires where at least 10% of the population is exposed. We then use a difference-in-differences (DD) framework to examine the impact of a wildfire. Municipalities that are at risk of a wildfire, however, are fundamentally different from those that never experience wildfire, most notably in size, as larger municipalities with higher density are less prone to wildfires than smaller ones close to wild lands. As such, we compare each treated municipality to those that will experience a wildfire later in our time period. Essentially, our results are identified from the timing of wildfires, rather than occurrence, which we found to be highly correlated with geographic, demographic, and financial characteristics of the municipality.

It is worth noting that the wildfires we examine in our analysis are more moderate than the recent severe years in California. Our financial data covers the period 1990 to 2015; to estimate five-year pre- and post-wildfire trends and impacts, we examine wildfires that occurred between 1995 and 2010. These wildfires destroyed an average of 872 structures per year. For comparison, 10,868 structures were burned in 2017 and 24,226 in 2018, making them large outliers. Our analysis is thus an indication of the impact of

[2] We focus on governments of incorporated areas, including cities and towns, but not county governments.

moderate wildfires, which are smaller, but more frequent and nonetheless damaging. Our findings are representative of the more typical wildfires experienced by municipalities, or if advances in forest management and fire prevention measures help constrain the size of future fires. If catastrophic wildfires increase in frequency in the coming years, however, our estimates will be a lower bound on future fiscal impacts. Even so, our findings provide an identification of the different channels of fiscal impacts on local governments, which allows for better projection of the impact of more severe events.

To identify whether any fiscal impacts were driven by population movements, we first estimate the migratory response to the wildfires. We find minimal net out-migration: a 0.78% decrease in population in the five years following a wildfire. Importantly, we estimate a five-year pre-trend of the treated municipality relative to the control municipalities. The estimated pre-trends in population are very flat and close to zero, which supports the key identifying assumption in a DD framework.

We then turn to examining the impact of wildfires on a range of revenue and expenditure categories. We find that total general revenues increase by 10.5% in the five years following the fire. Property tax revenues increase by 21.2%. This perhaps surprising result appears to be driven by the impact of California's Proposition 13 which artificially suppresses property assessments until time of sale. Wildfires lead to a turnover in housing, which allows for a resetting of assessments. Consistent with this explanation, we find a 57% increase in the real property transfer tax, which is a direct measure of transacted property values. We find sales tax revenues increase, which can be explained by rebuilding activities, likely supported by widespread insurance coverage for fire damages. We also find an average increase in functional revenues of 12.6% starting from the second year post-wildfire. This is mainly driven by special taxes, which require voter approval (and explain the time delay), whereas service charges and intergovernmental transfers are largely unchanged.

Along with the higher revenues, we also find higher expenditures post-wildfire. Total expenditures increase by 17.3%, largely driven by three categories of spending: public safety (up 18.5%), community development (up 40%), and transportation (up 17.8%). Interestingly, we see a persistently higher level of spending on community development and public safety, rather than a one-time response. The increase in community development spending is suggestive of the very long time frame of recovery. Decomposing the public safety spending, we find that expenditures on fire and disaster preparedness both increase dramatically over time, indicating a greater effort to invest in safety measures. However, they are only a small share of the total increase in spending, accounting for less than 5% of expenditures, and radically less than the firefighting costs incurred at the federal level.

The overall impacts on municipal budgets are negative. We find the net effect of wildfires is a decline in excess revenues of $97 per capita and a 25 percentage point increase in the probability of a budget deficit. The magnitude of the decline is large: 204% of the mean of excess revenues per capita (which is distributed around zero) and 10.7% of the per capita budget size. This is despite the buffering effect of a recovery characterized by minimal out-migration and good insurance coverage, an unexpected increase in property tax revenues, and the ability to raise additional revenues from functional taxes. This serves as a cautionary tale for future severe wildfires or wildfire-prone places in other states, where some of these favorable elements might not exist.[3] Indeed, in a robustness check, we find additional evidence that the more severe wildfires–those that impact a larger share of the population–have led to much more negative impacts on budget balance.

In another robustness check, we use an alternative definition of wildfire events, which is based on the total number of people affected and thus captures fires in larger municipalities where the absolute number of people impacted may be higher, but as a share of total population, is lower. We find similar effects in terms of population change, revenues, and expenditures, but only a small and insignificant effect on the budget balance. This suggests that our main results identify adjustments in budget components that are common across types of events and municipalities, but the overall effect depends on the size and fiscal capacity of the municipality. Larger cities can better buffer the fiscal shock of a wildfire, likely because, while possibly more damaging in absolute numbers, it is a smaller share of overall population and assets.

This paper contributes to three main strands of literature. First, a large body of empirical studies have investigated the economic impacts of natural disasters (see Kousky (2014)

[3]For instance, 90% of the population left the town of Paradise after the entire town burned down in the 2018 Camp Fire. The California Department of Insurance also reports that some home insurers have started charging higher premiums or canceling policies in high-risk zip codes in the state.

for a review). Most of this work has focused on aggregate macroeconomic impacts, often at the level of the country, but some papers look at more localized levels of government (Skidmore and Toya, 2002; Strobl, 2011; Hsiang and Jina, 2014; Boustan et al., 2017) or on household finances (Gallagher and Hartley, 2017; Deryugina et al., 2018; Farrell and Greig, 2018). Three papers look at more detailed budget impacts of disasters: Deryugina (2017) focuses on transfers to individuals, Miao et al. (2018) on state governments, and, closer to our analysis, Jerch et al. (2020), in a recent working paper, study how hurricanes affect the budgets of coastal cities. We provide novel estimates of budgetary impacts of wildfires at the municipal level.

Second, this paper contributes to research on wildfire mitigation activities, which appear to be largely under-invested in at the local level.[4] Prior work on this topic has largely focused on household level decision-making, highlighting low risk perceptions (Brenkert-Smith et al., 2006; Champ et al., 2013) and risk externalities between neighbors (Kunreuther and Heal, 2003; Shafran, 2008). A couple papers have also explored the incentive effects created by federal funding of wildland firefighting (Kousky and Olmstead, 2010; Baylis and Boomhower, 2019). We add to this literature in two ways. First, we provide evidence of disaster-driven increases by local governments in preparedness and planning activities, which may not be optimal (Anderson et al., 2018; Wibbenmeyer et al., 2019). Second, we find favorable impacts of wildfires on major revenue categories. This is consistent with Issler et al. (2019), who find that high insurance coverage of fire damage provides a strong incentive to rebuild and upgrade a destroyed home. While some of this may also be unique to California and the size of fire we study, this finding offers a plausible explanation for the perceived lack of local government interest in wildfire mitigation measures.

Third, this paper is also related to a public finance literature that analyzes how local budgets respond to shocks (Lutz et al., 2011; Skidmore and Scorsone, 2011; Alm et al., 2011; Cromwell et al., 2015; Feler and Senses, 2017; Jerch, 2018; Shoag et al., 2019). Most studies focus on macroeconomic shocks, such as the housing crisis or trade shocks, which primarily affect revenues. In contrast, we examine an exogenous shock

[4] Cases studies on local governments suggest they may not change their land use practices in response to a fire (Mockrin et al., 2018) or sea level rise risks (Shi and Varuzzo, 2020).

that directly impacts both spending and revenues. We find that municipalities are able to finance the fire-induced spending on reconstruction and defense through functional taxes and debt/reserve funds, with little evidence of crowding out other spending.[5] Moreover, our findings on property and transfer taxes add to another public finance literature on fiscal rules such as Proposition 13, which mostly focus on the direct impacts of such constraints (Shapiro and Sonstelie, 1982; Silva and Sonstelie, 1995; McGuire, 1999; Brunner and Rueben, 2001). Our results show that Proposition 13 interacts with a negative shock to create unexpected positive effects on municipal revenues post-fire, thereby providing distorted incentives for local governments in the context of natural disasters.

The remainder of this paper proceeds as follows. Section 2 provides background information and introduces the data. Section 3 presents the empirical design. Section 4 reports and discusses the results. Section 5 concludes.

2 Background and Data

2.1 Wildfires in California

California's most destructive fires often occur in the fall. This is when the long, hot, and dry summer has turned vegetation into tinder, and when the Diablo winds in the north and Santa Ana winds in the south can create warm, powerful gusts that spread wildfires. In recent years, higher temperatures have dried out more vegetation, the dry season has grown longer, and shifted wind patterns have fueled faster spread of wildfires, especially in Southern California. This has led some to conclude that California's "wildfire season" is now all year.

To measure wildfire exposure, we obtain GIS data on wildfire perimeters during 1990-2015 from the Fire and Resource Assessment Program (FRAP).[6] This program is run by the California Department of Forestry and Fire Protection (CAL FIRE) in collaboration with the United States Forest Service (USFS), the Bureau of Land Management (BLM), and the National Park Service (NPS). The FRAP database represents the most complete

[5]This is similar to the findings in Jerch (2018) regarding higher spending induced by federal mandates.

[6]For more detail of the FRAP database, visit https://frap.fire.ca.gov/frap-projects/fire-perimeters/.

digital record of fire perimeters in California. For each fire, we observe a range of variables including the year, the governmental agency responsible for managing the fire, the cause of the fire, and most importantly, a GIS layer depicting the area burned.

Figure A1 maps all wildfire perimeters in the FRAP database from 1995 to 2015. Wildfires are geographically widespread across the state. They tend to occur on vegetated wild lands outside of urbanized areas but the most costly fires are those close to developed areas. Commonly known as the wildland-urban interface (WUI), these are areas with low-density residential development intermingled with vegetation. California has vast areas of WUI. The 2019 Verisk Wildfire Risk Analysis estimates that more than 2 million properties in California are at high to extreme risk from wildfire. Despite the risks, many such areas in California are experiencing strong development pressure as the state struggles with an affordable housing shortage. Roughly 645,000 more houses are projected to be built by 2050 in locations currently designated as "very high" wildfire severity zones (Mann et al., 2014). In particular, Southern California appears to have the highest concentration of wildfires which likely results from conducive geographic and climatic conditions. Fires tend to occur closer to Los Angeles and San Diego more than other populous cities in the state.

When it comes to wildfire management, there are two broad categories of government responsibilities: firefighting and risk reduction measures. Responsibility for wildland firefighting falls on the agency that has jurisdiction over the ignition location and area affected (Hoover and Lindsay, 2017). In California, federal agencies are responsible for roughly 48 million acres of land and state agencies are responsible for 31 million acres. Together, they make up the vast majority of wildlands. Local governments, such as counties and cities, are primarily responsible for the protection of life and structures within their boundaries. Thus, they bear a smaller firefighting burden because the dense built environment within a city is more resistant to wildfire spread (Syphard et al., 2013; Price and Bradstock, 2014), and the presence of structures near the ignition location is associated with much greater efforts by the federal and state agencies to suppress the fire before it reaches property (Baylis and Boomhower, 2019). Some California cities do not have a fire-fighting function at all. In these cities, fire protection is assumed by special fire districts.

Activities to reduce wildfire risk, on the other hand, largely fall to local jurisdictions. There is no federal mandate on what local governments should do to manage wildfire risk (Mockrin et al., 2018). One of the most effective risk management tools, land use decisions, is inherently a local responsibility. It is not clear, however, if local governments have incentive to implement measures that either are costly or undesirable in the near-term. For example, restrictions on wildland development would constrain the city's tax base, building codes are often believed–correctly or not–to make construction more expensive, and vegetation clearing can reduce the amenity value of the location. Since municipalities bear only a small fraction of wildland firefighting costs, their incentives to lower risk may be weaker (Baylis and Boomhower, 2019). That said, wildfires could still threaten a city's fiscal health by reducing its tax base or forcing it to incur extra spending on rebuilding and emergency responses. We explore these channels here.

2.2 Municipal Finances in California

About 85% of California's residents live in one of the 482 municipalities in the state. Each municipality provides a variety of services to residents, including public safety, parks and recreation, flood protection, roads, sewers, water, and electricity, among other services.

We requested records on municipal budgets from the California State Controller's Office for fiscal years (FY) 1991-2016. By state law, all California municipalities are required to annually file the Cities Financial Transactions Report. These reports contain a detailed breakdown of municipal revenues and expenditures. There are two broad revenue categories in our data: general revenues and functional revenues. General revenues can be used for any legitimate purpose. The largest categories of general revenues are property tax and sales tax. Functional revenues, on the other hand, are restricted by law to a specific use. Examples include fees charged for public services as well as special taxes charged for transportation, parking, voter-approved indebtedness, etc. Table A2 provides a breakdown of revenue categories by source activity. Most expenditures are associated with one of the major service categories: public safety, general government, community development, transportation, culture and leisure, health, and public utilities. Table A3 provides descriptions of them.

The same data also contains information on city characteristics, such as estimated population, service responsibilities[7], and its governing system[8], among other variables. This data is crucial for studying wildfire impacts as cities that are most threatened by wildfires tend to be smaller. In the Annual Survey of State and Local Government Finances, another common source of local government data, smaller municipalities are only included once every five years. Our data, by contrast, allows us to fully observe the heterogeneity across California municipalities and particularly the large differences between those that face high fire risks and those that do not. We will discuss this point in more detail in Section 3 in the context of choosing the appropriate research design.

Property tax revenue in California municipalities is constrained by Proposition 13, an amendment to the state constitution passed in 1978. This proposition limits property tax rates to one percent and restricts annual increases in assessed property values to an inflation factor that cannot exceed 2 percent per year. Only when property is sold, or there is new construction, can there be a full reassessment of property value. If home prices appreciate at more than 2 percent, this creates a lock-in effect, where it is financially beneficial to remain in homes to avoid the higher taxes that come with reassessment (Wasi et al., 2005; Ferreira, 2010). Research has also found that Proposition 13 has decreased the reliance of local governments on property taxes (Hoene, 2004). The California Revenue and Taxation Codes allows property rebuilt after a natural disaster to retain its base year for property tax assessments, but reassessment applies if the property is then sold.

2.3 Dataset Construction

To create our municipality-year panel, we first construct an annual measure of wildfire incidence for each municipality. We calculate, using GIS shapefiles, the fraction of area in a census tract that overlaps with fire perimeters in each year.[9] We then multiply the fraction with the population in the census tract and aggregate to the municipality level using a crosswalk between census tracts and census places.[10] This yields a proxy of the

[7]Cities are classified into seven categories depending on whether they are responsible for parks, fire, and library.

[8]The cities are either chartered or governed by the state's general law.

[9]Source of census tract shapefiles: IPUMS NHGIS (Manson et al., 2019).

[10]Source of crosswalk: MABLE/Geocorr engine, http://mcdc.missouri.edu/applications/geocorr2014.html.

total population exposed to fire in a municipality, and we divide it by the total population to obtain the fraction of population exposed to fire. Using a population-weighted measure of wildfire exposure is preferable to a simple area-based measure, since it more closely captures those wildfires that have impacts on people and property.

We focus on those fires that impact more than 10% of the population in a municipality, referring to these as "major wildfires."[11] A large majority of them are in Southern California (Figure A2). Table A1 lists each of these incidents, the corresponding population exposure, and an alternative measure of area exposure by directly overlaying the shapefiles of cities and fire perimeters. The two measures show similar patterns of wildfire occurrences but imply different exposure intensity.[12] As expected, the area-based measure is larger in most instances, suggesting the fires tend to affect areas with lower population density. An important limitation of our exposure measure is that it tends to capture wildfire events in smaller municipalities and omit those in larger cities. In light of this, we undertake a robustness check using an alternative definition based on the total number of people affected. In this measure, larger cities with a wildfire may be treated, even when the relative share of impacted people and property is much smaller.

Finally, we merge the wildfire and finance datasets by municipality and year. The financial reporting is based on fiscal years, which run from July 1 of the previous year to June 30 of the current year. This means the wildfire season in the same calendar year actually occurs right after the end of the fiscal year. To account for this timing mismatch, we merge the financial observations to measures of wildfire incidences with one lag. For example, wildfires in year 2000 in the data are matched to financial data in FY2001, and the year is recorded as 2000.

[11] Note that a big wildfire might impact multiple municipalities at the same time, and we consider each a separate event. Fillmore, Malibu, and Moorpark experience more than one wildfire. We count the most significant one ranked by the population-based measure of wildfire exposure.

[12] There is one case (Colfax in 2001) where the city and fire shapefiles do not overlap at all. This might be a case of fire affecting communities living right at the edge of a small city.

3 Research Design

3.1 Exposed vs. Control Municipalities

A standard approach for estimating the causal impacts of exogenous shocks like natural disasters is a difference-in-differences (DD) framework. In our context, this would compare exposed and control municipalities before and after the wildfire.[13] Identification in this framework typically relies on the parallel trend assumption, namely that the outcomes of treated and untreated units will have parallel developments absent the treatment.

In our context, however, it is nontrivial to choose a control group that satisfies the identifying assumption. The municipalities that have experienced wildfires are different from those that have not on a number of dimensions. Table A4 presents the summary statistics of the two groups for comparison. Even after excluding San Francisco as a clear outlier, the unexposed cities are much larger across multiple measures: their average population is almost twice as large, and their revenues and expenditures are three to five times as large on a per capita basis. They are also much more likely to be charter cities (23.0% vs. 2.9%) or full service (25.2% vs. 4.7%), which is largely determined by city size. While large level differences themselves do not invalidate the parallel trend assumption, they reflect that the two groups of cities could be at different stages of development and their budgets might evolve differently.[14]

These observable differences suggest that wildfire occurrences might be correlated with other unobservable characteristics that are important for the municipality's development trajectory. This presents substantial challenges to using unexposed municipalities as our control group.[15] Therefore, we define our control group as municipalities that expe-

[13] In particular, there is a sizable literature using a staggered DD framework to examine the effects of natural disasters occurring in different location and time. Recent examples include Deryugina (2017), Gallagher and Hartley (2017), Hsiang and Jina (2014), and Boustan et al. (2017).

[14] Some studies have found that cities follow Gibrat's Law, which holds that that proportional population growth rate and initial size have no relationship (Eeckhout, 2004). Recent investigations suggest the contrary for American counties and metros (Desmet and Rappaport, 2017). In any case, Gibrat's law is not likely to hold for revenues and expenditures as they are determined not only by population but also by city service requirements.

[15] We have also explored using DD on a matched sample, where we non-parametrically match each exposed city with unexposed cities that are closest in selected characteristics to it. However, even after match-

rience a wildfire at a *later* point in time than our treatment municipalities. Specifically, our sample is constructed as follows. We start with the panel of all municipalities exposed to a wildfire during 1995-2015. For each wildfire incident before 2010, we construct an incident-specific dataset of one treatment unit (the exposed municipality) and several control units (other municipalities that will not experience a wildfire within 5 years but do, at a later point in time, experience a fire). This dataset includes observations from a specified period around the treatment time. These incident-specific datasets are then stacked together to form the final dataset. In this construction, validity of the treatment-control comparison requires the assumption that the financial conditions of all (about-to-be) exposed municipalities follow similar trajectories absent the incident, and the timing of the incident is assumed to be random. In past applications, this design has been shown to be effective in settings where the treated units are fundamentally different from the untreated units. Examples of such treatments include health shocks (Fadlon and Nielsen, 2019), closings of a Social Security Administration field office (Deshpande and Li, 2019), and desegregation of school districts (Guryan, 2004).

3.2 Econometric Framework

The estimating equation takes the form

$$Y_{iwt} = \sum_{\tau} \beta_\tau Fire_{iw} \times EventTime^{\tau}_{wt} + \delta_i + \delta_t + \varepsilon_{iwt}, \tag{1}$$

where i denotes the municipality, w denotes the wildfire event, and t denotes the calendar year. Y_{iwt} is the outcome of interest, which could be population or various revenue and expenditure items on the municipal budget. We apply an inverse hyperbolic sine transformation ($asinh$ hence force) to most of these outcomes. This allows us to interpret the coefficient in percent terms while retaining true zero-valued observations as sometimes seen in small budget categories.[16] $Fire_{iw}$ equals one if i is the exposed municipality in

ing, we still observe a differentially increasing pre-trend for the exposed cities. Moreover, matching could be problematic due to a regression-to-the-mean bias (Daw and Hatfield, 2018).

[16]We calculate the percent change in outcome variable using the following adjustment: $\Delta Y\% = e^{\hat{\beta}-0.5v\hat{a}r(\hat{\beta})} - 1$. This is a standard logarithmic adjustment for semi-logarithmic regressions with dummy

event w, and zero otherwise. $EventTime^{\tau}_{wt}$ is a set of indicators that identify the year relative to the fire. For example, $EventTime^{3}_{wt}$ will be equal to one if time t is three years after the fire in event w, and zero otherwise. We let τ goes from -5 to 4 so that we observe five years each in the pre- and post-fire periods. Lastly, γ_i denotes a municipal fixed effect, which controls for time-invariant municipal characteristics of finances, geography, and underlying wildfire risks. γ_t is calendar year fixed effect, which controls for aggregate shocks over time, such as those from macroeconomic conditions or changes in state law and policy. Given that we have the same municipalities appearing multiple times in different events and time frames, we will also show that our estimates are robust to the inclusion of incident fixed effects. Throughout the paper, we cluster the standard errors at the wildfire incident level. This accounts for the main source of variation in wildfire incidents as well as from sample construction.

The β_τ's are our variables of interest. The identification of these coefficients relies on the assumption that the treatment and control units will follow parallel trends absent the treatment. Importantly, the pre-period indicators allow for full flexibility in the pre-trends. Therefore, we can assess, based on their coefficients, whether the treatment and control units have parallel trends prior to the treatment. A parallel pre-trend does not guarantee the key identifying assumption will hold but greatly lowers the concern of bias due to differential trends.

Recent econometrics research shows that two-way fixed effects (TWFE) models may lead to biased estimates due to treatment effect dynamics or cohort heterogeneity (e.g. Goodman-Bacon, 2018; Callaway and Sant'Anna, 2019; de Chaisemartin and D'Haultfœuille, 2020; Baker et al., 2021). This literature illustrates that it is problematic to use earlier treated units in their post period as control units when they are evolving under time-varying treatment effects. While equation (1) is a TWFE specification, our sample only allows for comparing earlier treated units with later treated units in their pre-period by construction and thus our estimates are not contaminated by such problematic comparisons. However, it is worth noting that our estimates are still subject to unequal weighting of treatment effects implicit in the regression design.

variables (Kennedy et al., 1981). As our outcomes are all measured in dollars, the values are large enough to apply this adjustment with little error (Bellemare and Wichman, 2020).

We also run a standard DD estimation equation which takes the form

$$Y_{iwt} = \beta Fire_{iw} \times Post_{wt} + \delta_i + \delta_t + \varepsilon_{iwt}, \tag{2}$$

where the event-time indicators are replaced by $Post_{wt}$, which is equal to one for the entire post-fire period in event w, and zero otherwise. β represents the five-year average effect of a wildfire incident. Estimates from this specification are reported in the tables to provide a concise summary of effect sizes.

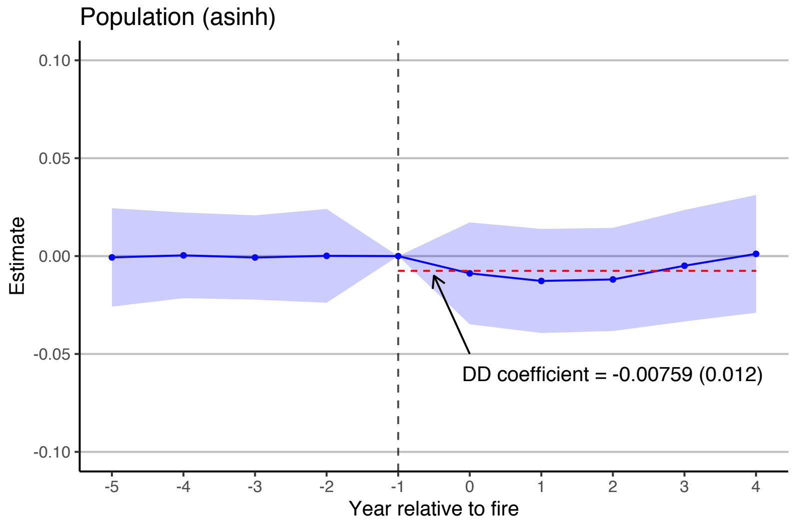
4 Results

4.1 Population

Natural disasters might induce migration responses. After a major fire event, homeowners may choose to relocate, either due to an increase in risk perceptions or a response to damage or community disruption. In understanding any impact on revenues or expenditures, it is important to estimate if any fiscal changes are due to population changes in the municipality. We thus begin by estimating population changes in wildfire-impacted municipalities.

Figure 1 plots the event study estimates from equation (1) and their 95% confidence intervals in blue. The outcome variable is population after $asinh$ transformation. The vertical dashed line at -1 indicates the likely timing of the wildfire incident, as the wildfire season is usually at the beginning of the current fiscal year (July 1). Examining the results, the estimates of period -5 to -1 are almost perfectly aligned with the horizontal reference line at 0, suggesting very little difference in how population evolves in the treated and the control cities before the fire. Starting from period 0, the year of the fire, the estimate takes a small dip, stays low for three more years, and returns to align with the pre-trend at the end of year 4. While the dip is certainly visible, its scale is small and none of the estimates are statistically significant. The corresponding DD estimate confirms this finding. As shown by the red horizontal line, the point estimate suggests that the average drop in population

Figure 1: Wildfire impacts on population



Notes: this figure shows point estimates from equation (1) and their 95% confidence intervals in blue, and the point estimate from equation (2) in red. The dependent variable is $asinh$-transformed population. Statistical significance for the DD coefficient: *p<0.1; **p<0.05; ***p<0.01.

in the five years following the incident is 0.78 percent.[17] This suggests that fire-exposed municipalities experience only very minimal net out-migration, which they recover within five years.

How does our estimate compare to the literature? To our best knowledge, this is the first estimate of municipal migration response to wildfire. The closest estimate is provided by Boustan et al. (2017), who find that the occurrence of a wildfire during 1980-2010, on average nationwide, increases a county's net out-migration rate by 3.1 percentage points. We estimate a much smaller and more short-lived effect. There are several reasons to expect this discrepancy. First, effects in California could be lower because of unaffordable housing costs in many more densely developed communities that limit abilities to relocate out of the given community. Second, the population measure in Boustan et al. (2017)

[17] Following Kennedy et al. (1981), the implied percent change is calculated as $e^{0.0759-0.5*0.012^2} - 1 = 0.078$.

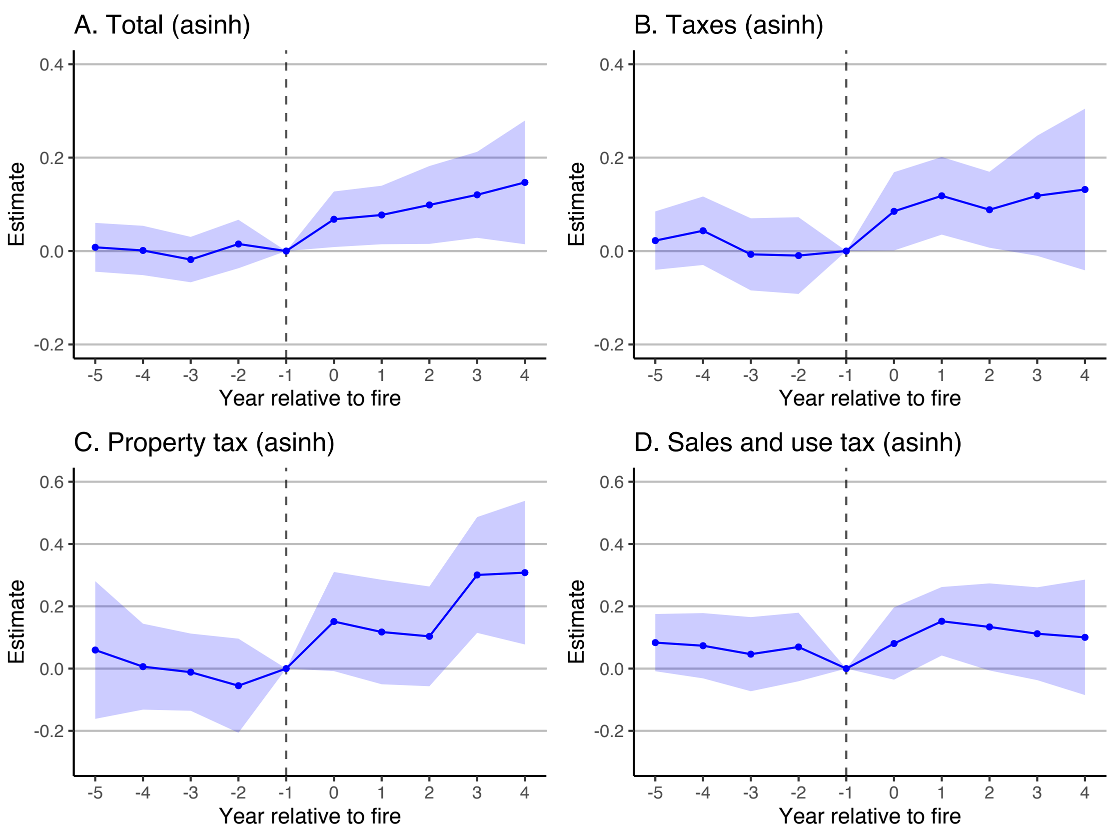
includes all county residents regardless of whether they live in an incorporated area. The gap between our estimates might reflect a difference in migration responses across the city boundary. Outside the city where development density is lower and wildfire risk is higher, migration responses might be larger.

While there is little change to the total population, the demographic composition of the population might change as different groups might move in or out of these communities in response to the fire. To examine these changes, we calculate the average profiles of home buyers in each municipality and year using mortgage records from the Home Mortgage Disclosure Act (HMDA). We focus on the average income, race, and ethnicities of the mortgage applicants, as well as whether the home would be owner-occupied. Table A5 reports the DD estimates on these outcomes. We see very little change in the average income or occupancy choice of the home buyers following the fire, but there appears to be an increase in the fraction of Hispanic buyers by 2.8 percentage points and a compensating decrease in white buyers. This change is potentially policy relevant, but the implications are beyond the scope of this paper. Since this affects less than 0.5% of the total population in each year, we believe the shift is unlikely to change municipal budgets in substantive ways. In addition, the preferences of the new residents would not manifest in immediate budget changes, such as we are observing below. Any impacts we find in the subsequent analysis on municipal finance, therefore, are not likely due to changes in population.

4.2 Revenues

We start with general revenues. Figure 2 plots our estimates based on equation (1) for four outcomes: total general revenue, revenue from all taxes, property tax revenue, and sales tax revenue. The corresponding DD estimates are reported in Table A6. All four panels show a relatively flat pre-trend, again providing support for the identifying assumption. In Panel A, we see an increase in general revenues of 6.8% in the year of the fire. The increase then gradually grows over time and reaches 14.7% by the end of the fourth year. The DD estimate shows a 10.5% average increase over five years. In Panel B, there is a similar increase in revenue from taxes, which accounts for the majority of general revenues. When we further explore the two largest tax categories in Panel C and D, we see a larger increase

Figure 2: Wildfire impacts on general revenues



Notes: this figure shows point estimates from equation (1) and their 95% confidence intervals. Each panel corresponds to a major revenue category displayed above the plot.

in property tax revenues averaging 21.2% over five years, and an increase in sales tax of 10%.

The increase in sales tax is likely due to increased spending on rebuilding. Homeowners insurance, which covers wildfire damage, is widespread, so many victims will have insurance proceeds to fund rebuilding and repair. Reconstruction activities and additional purchases to replenish lost items might increase local spending and employment, which, in turn, would account for the increase in sales tax revenues. Two years after the fire, the revenues from sales taxes start trending back down, which is consistent with the rebuilding activities slowing. An increase in sales tax revenue was also observed after hurricanes in

Alabama (Handley, 2006).

The results for property values, however, may initially appear surprising. Prior work has found housing values can decline post-disaster, although price effects from wildfires have been found to be short-lived (McCoy and Walsh, 2018; Garnache and Guilfoos, 2019). There are a couple possible explanations for our findings given that we found in Section 4.1 that post-wildfire population changes were minimal. One possibility is that, while some areas impacted by wildfire lose value, other safer areas in the same municipality gain in value. For example, areas with higher structure density are safer from fire spread and might become more desirable (Syphard et al., 2013; Price and Bradstock, 2014). Moreover, Issler et al. (2019) show that homeowners have a strong incentive to rebuild their damaged homes to the latest building code since the cost is often covered by insurance. This, in turn, could lead to an increase in home values.

We find it most likely, however, that the explanation of our result comes from Proposition 13. As noted above, Proposition 13 artificially suppresses property assessments in California until the time of sale. Zillow has estimated that the market value of an average California home is 85% higher than its assessed value (Terrazas, 2018). As such, property sales account for about three quarters of the growth in statewide property tax revenue during our sample period, according to a back-of-the-envelope calculation.[18] If the wildfire increases transaction volumes, it could generate higher property taxes for the municipality through this mechanism.[19] Note, that even if the wildfire led to some decrease in value, if that was less than the amount by which the assessment was suppressed, there would still be an increase in property taxes after post-wildfire transactions. In Colorado, McCoy and Walsh (2018) has found that home transactions increase as the housing market adjusts after a fire. While we do not have housing transactions data for our time period in California, we can test this mechanism by examining property transfer tax revenues. This tax is charged on the transfer of interests in real estate and hence is a proxy of value-weighted transaction volumes. Although the estimates are noisy,[20] we find a large relative

[18] The average property tax revenue growth is about 8%, of which 2% is the automatic adjustment in assessment value and the rest comes from home sales and development (Alamo and Whitaker, 2012).

[19] In California, homeowners whose properties are damaged by natural disasters are exempt from reassessment. However, if the house is sold after reconstruction, the provision no longer applies.

[20] Estimates on relatively smaller tax categories are more prone to measurement errors.

increase in property transfer tax revenues of 57% in the five years following the fire (Figure A3). A back-of-the-envelope calculation suggests this plausibly explains our finding of a roughly 21% increase in property taxes. California's housing turnover rate is around 8% during our sample period, implying additional transactions of 4.6% of the homes annually, or 23% over five years. Assuming the assessed values of these homes increase by 85%, this amounts to a 19.6% increase in the property tax base, which is close to our estimate. Furthermore, the dynamics of the transfer tax match those of property tax revenues – an immediate increase followed by a second increase in event year 3 – which also provides strong evidence that the change in property tax revenues is related to higher transaction volumes.

Next, we examine functional revenues. Figure 3 plots the event study results on total functional revenues and its three largest components by collection mode: special taxes, service charges, and intergovernmental transfers.[21] The corresponding DD estimates are reported in Table A7. In Panel A, the point estimates indicate a 7% drop in functional revenues in the year of the fire, which is then followed by a 13-18% increase in the subsequent four years. The increase is mainly driven by revenues from special taxes (Panel B), which shows an increase of over 213% starting from the second year. Current service charges and intergovernmental transfers remain unchanged.

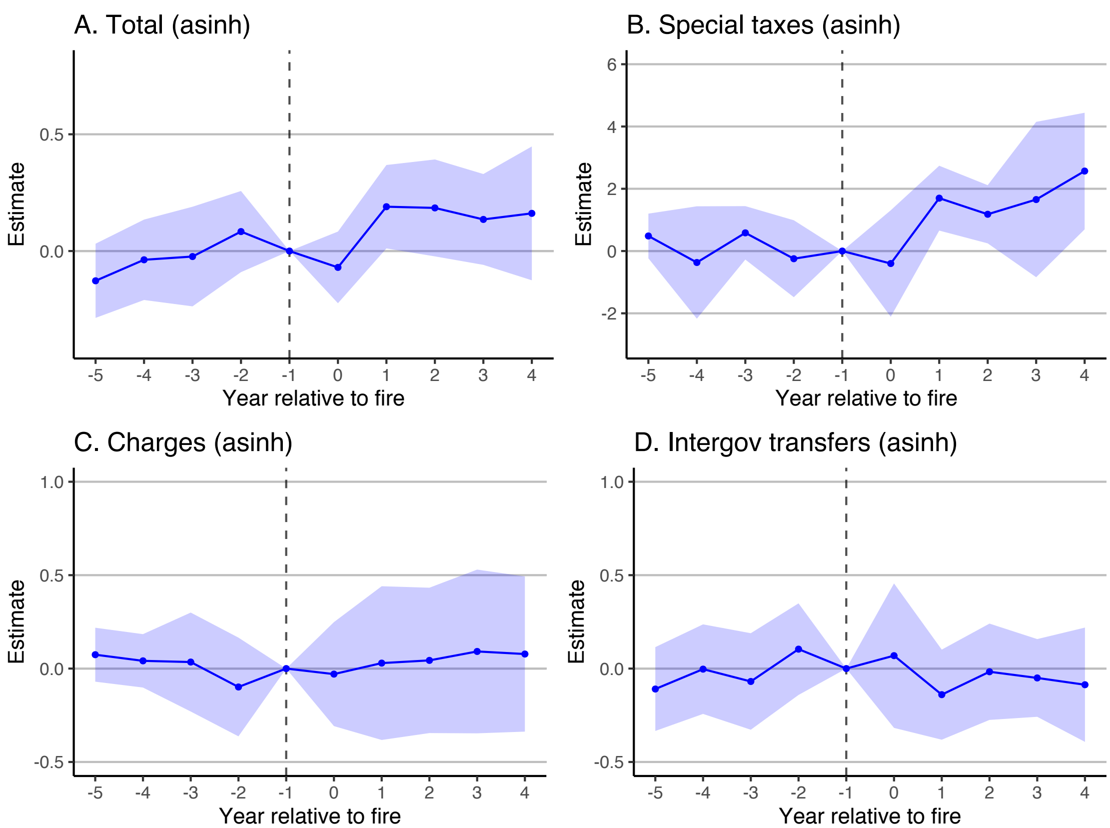
Compared to general revenues, a notable difference in the dynamics of functional revenues is a one-year lag in impacts. A possible reason for this is that while an increase in general revenues largely stems from an increase in the tax base, changes in functional tax revenues are more likely to stem from tax rate increases or the introduction of a new tax.[22] In California, these measures require two-thirds approval by voters.[23] The vote requirement would delay additional revenue collection by at least one year. In the next section, we examine whether city governments are incurring higher costs that may explain these tax increases.

[21] This is the sum of all functional revenues from intergovernmental transfers from the federal, state, and county governments.

[22] Some recent examples of such tax measures include a special sales tax in Sonoma County (https://sonomacounty. ca.gov/CAO/Fire-Services-Project/) and a special parcel tax proposal in Los Angeles County (https://www.latimes. com/california/story/2019-12-03/fire-department-parcel-tax-increase-ballot).

[23] California Constitution, article XIIIC, section 2.

Figure 3: Wildfire impacts on functional revenues



Notes: this figure shows point estimates from equation (1) and their 95% confidence intervals. Each panel corresponds to a major revenue category displayed above the plot.

Overall, we find wildfires increase both general and functional tax revenues. This results from a combination of factors, including: (1) minimal impact on population and the tax base; (2) the interaction between housing market adjustments and Proposition 13; and (3) the ability of city governments to raise revenues through special taxes. We caution, however, that results could be noticeably different in states without limits on property tax assessments or for more severe fires that damage a larger portion of the community.

4.3 Expenditures

In this section, we examine expenditures for different service activities. Figure 4 plots the event study estimates on expenditures in total and by major activity category. The corresponding DD estimates are reported in Table A8.

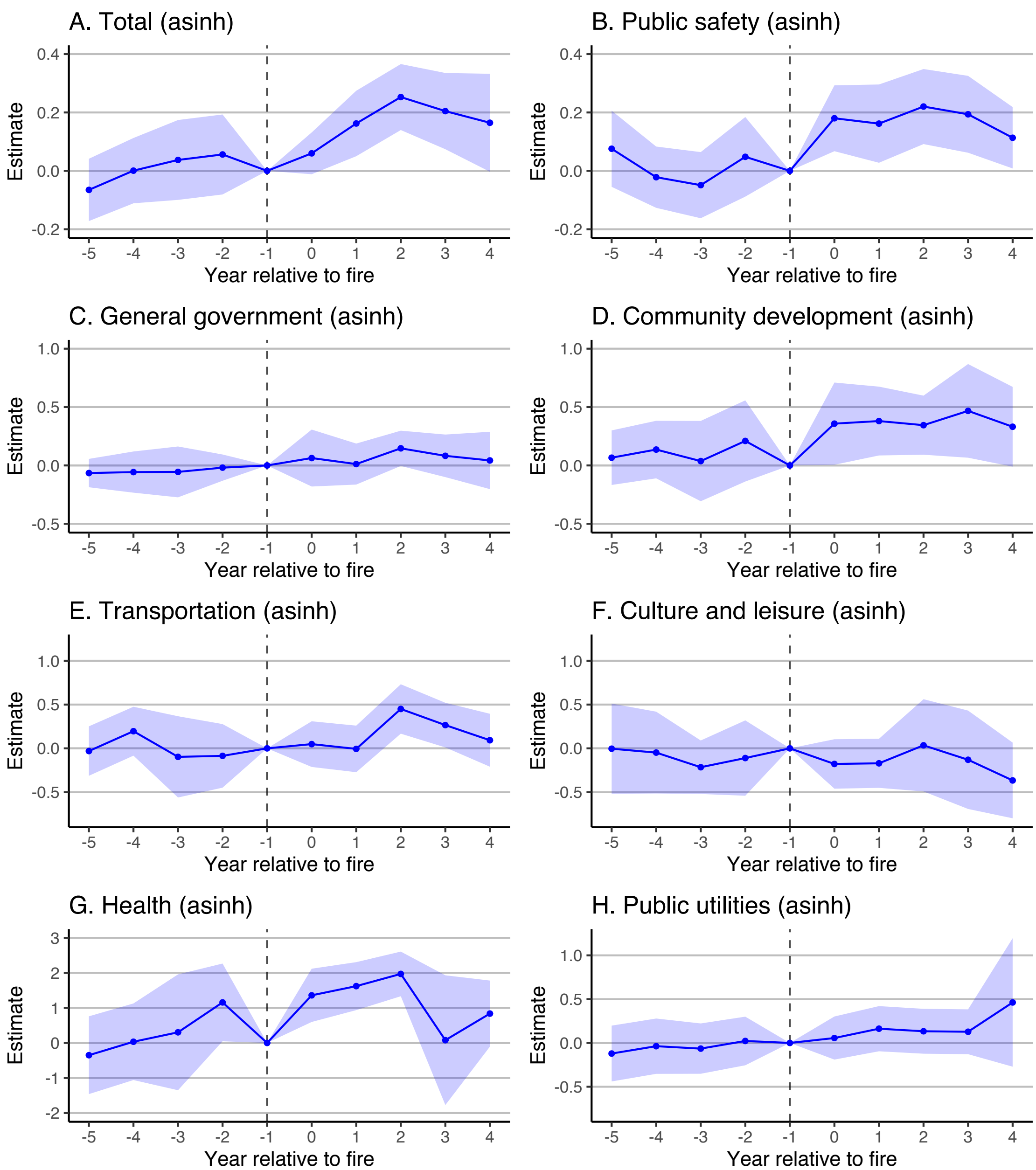
In Panel A, total expenditures start increasing after the fire, peaking at the end of event year 2 at around 25%. The average increase is 17.6% over five years, or about $5.9 million US dollars for an average municipality in the sample. Among the activity categories, public safety (Panel B) and community development[24] (Panel D) show the largest changes with both immediately increasing and then stabilizing at a higher level throughout the five years post-wildfire. The average increase is 18.5% for public safety (or about $1.4 million) and 40% for community development (or about $1.6 million). Both categories contain spending on activities that are highly relevant for post-disaster response, which we explore in more detail below. Public safety includes police, fire, emergency services, and disaster preparedness. Community development includes building, permitting, code enforcement, and planning. Another category, transportation (Panel E), sees no change for two years and a sudden and large increase of about 50% in the third year. It is possible that extra expenditures are needed to repair transportation infrastructure damaged by the fire, but the reason for the two-year delay in spending is unclear.

Unsurprisingly, we do not find an increase in general government spending (Panel C), as regular administrative functions are largely insulated from wildfire impacts. Expenditures on culture and leisure (Panel F) and public utilities (Panel H) also stay the same, which suggests that the fires exert minimal impact on these categories. The estimates for health expenditures (Panel G) show a large increase following the fire. However, the overall erratic pattern suggests there might be underlying data challenges. A plausible explanation is that some recorded zeros are actually missing values that have been treated as true zeros by the $asinh$ transformation.[25] We explore this possibility by estimating how

[24] We remove three observations of zeros in the regression for community development. They are repeated observations of the same city and year. In the raw data, this observation is an isolated zero in the time series and, therefore, more likely to be a missing report than a true zero. Including these observations leads to negative estimate for event year -4 that is large in scale and very noisy, but creates no notable changes to other estimates.

[25] In the raw data, smaller items are recorded as missing when they are not reported. However, since

Figure 4: Wildfire impacts on expenditures



Notes: this figure shows point estimates from equation (1) and their 95% confidence intervals. Each panel corresponds to a major expenditure category displayed above the plot.

the "extensive" (whether the observation is nonzero) and "intensive" (estimation based on only nonzero observations) margins of health expenditures change after the wildfire (see Figure A4). Given the similarity between the overall dynamics and those of the extensive margin, it is clear that the number of non-zero observations in each period drives the estimates. Therefore, we believe it is problematic to interpret these estimates as causal effects of wildfire incidents on health expenditures. Overall, it is notable that the services most related to post-fire reconstruction have substantially greater spending while there is no corresponding decline in other categories. This suggests that the government did not move funds from other services to finance the increased spending.

The persistence of higher levels of expenditures on community development and public safety suggests two things. First, disaster recovery, as many emergency managers note, is a long-term process that can take years. We see in our data at least five years of higher spending on community development post-fire, which most likely represents a range of spending to help rebuild the economy and public goods of the community. Indeed the manager of a town which suffered a recent wildfire noted in personal communication that the rebuilding needed after a wildfire always tends to lead to a jump in community development spending. Second, there could be an increase in disaster preparedness efforts motivated by the salience of wildfires, as we see in the public safety spending increase. This aligns with one prior study, which found that in eight locations across the U.S., communities increased wildland firefighting, emergency response, and hazard planning documents following a wildfire (Mockrin et al., 2018). We further examine this possibility in our data.

Specifically, we analyze two subgroups of activities classified under public safety: fire and disaster preparedness. The fire category includes all expenditures related to the suppression and prevention of fires (*e.g.* administration, suppression, prevention, training, communications, buildings and equipment). The disaster preparedness category includes all expenditures related to the development and maintenance of a local disaster preparedness plan. Note that both are small expenditure categories with many zero observations, such that results based on $asinh$-transformation might not be reliable (Bellemare and

total health expenditures is an aggregate item, missing values are recorded as zero, which creates some drastic swings in health expenditures across years. We do not see this pattern for other aggregate spending categories.

Wichman, 2020). For robustness, therefore, this analysis examines not only total expenditures in $asinh$-transformation (similar to above) but also in levels.

Figure A5 plots the event study estimates for these outcomes, with the corresponding DD estimates and implied percent changes reported in Table A9. Panel A shows a clear and persistent increase in the $asinh$-transformed total fire expenditures, with the magnitude of a 286% increase from the pre-fire level. In levels, this increase is $686,000 dollars as shown in panel B, which represents a much smaller relative increase of 75.5%. For disaster preparedness, we also observe a continuous increase in spending in both panels C and D. Again, the estimate based on the $asinh$-transformed outcome implies a much larger relative increase at 721%, while the estimate based on the outcome in levels suggests an increase of $57,000 dollars, or 164% of the baseline.

The discrepancies in the implied percent change across estimates for the same spending category substantiate our concern regarding the $asinh$-transformation for these categories. We thus urge caution in interpretation. Moreover, fire and disaster preparedness are a small share of overall budgets, only accounting for 4.3% and 0.15% of overall municipal expenditures, respectively. As such, they are not a substantial contributor to the overall observed increase in expenditures. Indeed, given the small absolute values of spending in these categories, even large percent changes amount to small impacts on the budget. Nonetheless, the patterns from these results are telling: we do not see a one-time spike in spending, which - consistent with previous studies - suggests the increase is not due to real-time firefighting costs. Instead, the persistent increase we observe likely represents greater investments in preparedness, planning, and emergency response, which suggests a post-fire shift in perceptions about the need or desirability of such expenses. Such salience-driven responses are commonly observed for low-consequence, high-impact events but could be inefficient (Gallagher, 2014; Anderson et al., 2018; Wibbenmeyer et al., 2019). We do not have the ability to determine economically optimal risk reduction expenditures with our data.

To conclude this section, we find a large increase in total expenditures following a major wildfire incident. This increase is mainly driven by increased community development, transportation, and public safety spending. We find no evidence that the increase in these categories crowds out other spending. Community development represents the largest increase, and this is related to longer-term recovery spending. We also find evidence that the wildfires prompted municipal governments to invest in long-term adaptation measures related to fire and disaster preparedness.

4.4 Budget Balance

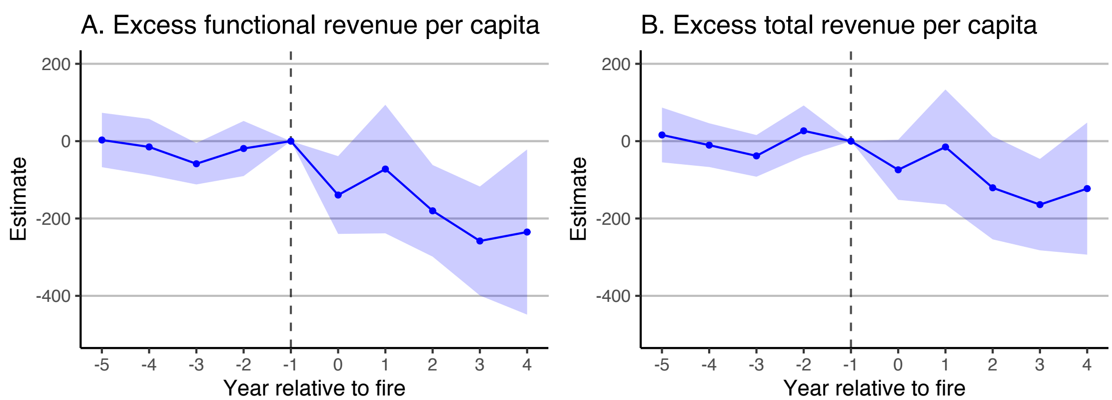
In the previous two sections, we find that wildfires lead to both higher revenues and higher expenditures. In this section, we examine the overall impact on municipal budgets.

We focus on two key outcomes: (1) excess functional revenues per capita, which is calculated by subtracting total expenditures from functional revenues and then divided by total population; (2) excess total revenues per capita, which is obtained by applying the same procedure to total revenues. As many observations for both variables are negative[26], it is difficult to interpret results using the $asinh$-transformed dependent variable. Instead, we examine the levels of these variables directly. On average, cities are able to balance their budget and build up some reserve. Among wildfire-prone cities and over the entire period of 1990-2015, the average excess revenue per capita is positive and only about one third of city-year observations have a deficit (Table A4).

The event study estimates are plotted in Figure 5, and the corresponding DD estimates are reported in Table A10. In Panel A, we see the event study estimates are negative throughout the five years after the fire and the deficiency is growing. On average, the deficiency has grown by $168 per capita. This shows that the increase in functional revenue post-wildfire is not able to offset the increase in expenditures. For excess total revenues per capita, we expect the estimate to be smaller in scale or even positive, given that general revenues have also increased after the fire. Panel B shows a similar pattern but a smaller decrease, averaging at $97.1 per capita over the five years. This indicates that larger general revenues help mitigate budget imbalance but also fail to completely offset the larger expenditures. The increase in the overall deficit is very large (204%) compared to the mean of the dependent variable, which distributes around zero. When compared to the overall budget size, it amounts to 10.7% of total revenues per capita, which is substantial.

[26] Specifically, 93% of excess functional revenues per capita and 29% of excess total revenues per capita are negative.

Figure 5: Wildfire impacts on budget balance



Notes: this figure shows point estimates from equation (1) and their 95% confidence intervals. The dependent variable is per capita functional revenues in excess of expenditures in Panel A and per capita total revenues in excess of expenditures in Panel B, both in levels.

We also examine the probability of having an overall budget deficit, that is, when excess revenues are negative (Figure 6). Not surprisingly, we find a higher probability of having a budget deficit following the fire. The average increase over five years is 25 percentage points, which is quite large compared to the mean in the present sample (0.29) and the mean in the panel of all municipalities (0.38).

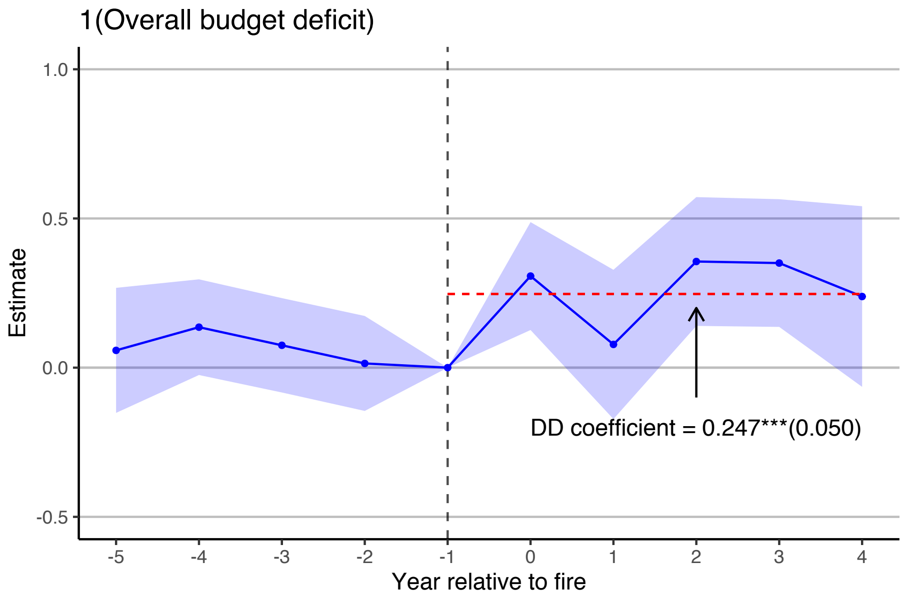
Together, our estimates show that wildfires increase budget challenges for municipal governments. Both the decrease in excess revenues (increase in deficiency) and the increase in the probability of a budget deficit are substantial. A small part of this effect could be attributed to increased investment in fire preparedness, which might be welfare-improving. However, the effect we observe appears largely driven by rebuilding activities to recover from wildfire damage.

4.5 Additional Analyses

This section reports findings from a couple robustness checks, as well as analysis of heterogenity in response.

Incident fixed effects. By construction, a later-exposed city can appear in the sample

Figure 6: Wildfire impacts on the probability of overall deficit



Notes: this figure shows point estimates from equation (1) and their 95% confidence intervals in blue, and the point estimate from equation (2) in red. The dependent variable is an indicator of having an overall budget deficit. Statistical significance for the DD coefficient: *p<0.1; **p<0.05; ***p<0.01.

multiple times in different periods as a control city for earlier-exposed cities. To limit the extent a city is compared to itself in an earlier period, we estimate an alternative specification with an additional incident fixed effect. Table A11 reports the DD estimates on five major outcomes: population, general revenues, functional revenues, total expenditures, total excess revenues. The point estimates are almost exactly the same as the main results.

Population weights. Weighting by population is often used with the stated goal of obtaining a population average effect in the presence of unmodeled heterogeneous treatment effects. While it often falls short of this purported goal, comparing weighted and unweighted estimates is useful for gauging the extent of mis-specification in the model (Solon et al., 2015). Recall that our sample consists of incident-specific sub-samples. We weigh all observations in each sub-sample by the population of the exposed city one year prior to the incident. Table A12 reports the DD estimates on the same five outcomes as above. Again, the estimates are quite similar to our main results.

Fire events defined by the number of people affected. So far in this paper, we have defined major wildfire events as those affecting more than 10% of a municipality's population. As exposure is measured against the size of the municipality, one concern is that the measure could be biased toward wildfires in smaller municipalities while ignoring those that affect a larger absolute number of people in a large municipality. As a robustness check, we repeat the analysis but define a major fire as one that affects more than 5,000 people. There are 17 such events between 1995 and 2010, including 7 shared fires with our main definition but also fires that burned in large cities such as Los Angeles, San Diego, and San Bernardino. Table A13 reports these results, which shows a similar qualitative pattern as before with no significant effect on population but an increase in both revenues and expenditures. The main difference is that the budget appears to be better balanced with a small and insignificant estimate. These results suggest that wildfires affect the overall budget of municipalities through similar pathways, but they are less disruptive to large cities. That is, smaller municipalities appear less able to buffer the fiscal shock.

Heterogeneous severity. So far in this paper, we have focused on a binary measure of a major wildfire incident. However, there might be non-linear relationships between some outcomes of interest and the size of the fire's impact on the community. We examine this by splitting the DD indicator in equation (2) into two groups, one indicating the five fires that have a population exposure over 20% ("severe fire"), and the other indicating the twelve fires with 10-20% population exposure ("other fire"). Table A14 reports estimates from the same set of major outcomes as above. We find similar estimates for the two sets of fires on population and general revenues. In particular, the estimate on general revenues for severe fires is noisy and statistically insignificant, but the magnitude is very similar to the other fires. This suggests that the mechanism of Proposition 13 is also likely at play, though not further amplified to create more positive effects. We do, however, find a marked difference between the severe fires and others in the remaining outcomes. The severe fires are not associated with any increase in functional revenues. Moreover, the increase in expenditures following a severe fire is half the effect of other fires. Together, these results suggest that cities affected by a severe fire might have more difficulties financing the extra spending needs induced by fire. Indeed, severe fires have a much larger impact on budget balance than the others. Column (5) shows the decrease in excess revenues is \$166 per capita following severe fires compared to \$61 following the other fires.

5 Conclusion

In this paper we investigate the impact of wildfires on municipal revenues and expenditures. The wildfires in our sample are modest compared to the devastating blazes that California experienced in 2017 and 2018. Still, they are indicative of the majority of wildfires and provide a lower bound on impacts from more severe fires. We find that historical wildfires during 1991-2010 increased both revenues and expenditures in certain categories, but the overall impacts on a municipality's budget were negative. This suggests that even modest wildfires can be fiscally harmful to local governments but we also find the budget impacts are worse for wildfires that impact a larger share of the population. The negative fiscal impacts of wildfire may also be more pronounced outside of California, since one of the main sources of increased post-wildfire revenues in our sample is due to unique legislation in the state.

We examine wildfires that impact at least 10% of a municipality. We find minimal net out-migration, which suggests fiscal impacts are not driven by population changes. We find an increase in property tax revenue, likely explained by California's Proposition 13. We see an increase in property transfer taxes post-wildfire, suggesting the fire leads to greater home sales. Proposition 13 artificially suppresses property assessments until time of sale. It thus appears that this policy leads to a surprising increase in property tax revenue post-wildfire due to updated property assessments from larger numbers of sales. Even if the wildfire depresses property values, we find this effect of reassessments to outweigh any decline from the fire. This is unlikely to occur outside California. Sales taxes also increase, suggesting increases in spending for post-wildfire rebuilding and replacement of damaged items. Widespread insurance coverage for fire likely facilitates this type of spending soon after the disaster.

We also find that municipal governments raise additional revenues after more moderate wildfires through functional taxes. They also increase spending on multiple categories, most notably community development and public safety. This increased spending suggests that disaster recovery can take years, as community development expenditures remain elevated, and also that there is a heightened risk perception by local policymakers or a belief that prior levels of spending on these activities were insufficient, such that disaster preparedness activities increase.

Overall, the impacts on the municipal budget are negative. This is particularly true for smaller municipalities located in or near WUI, who might have a more difficult time adjusting to fiscal disruptions created by a wildfire. While in our sample period there was not a notable case of a municipal government falling into severe financial distress due to wildfires, wildfires are still on net costly. Financial ratings firms have generally reported confidence in local governments honoring their debt obligations after such events, citing insurance proceeds, intergovernmental aids, and the locality's own resource funds as mitigating factors for short-term impacts.[27] That said, some municipal debt was downgraded after the 2017 and 2018 wildfires in California, which took a much more severe toll on a few municipalities.[28]

The findings of this paper add to our understanding of the incentives of local governments to invest in fire mitigation. On the one hand, we find that wildfires have a negative and substantial net impact on municipal budgets. It would thus be in a municipal government's interest to mitigate such risks. However, local governments are also largely shielded from the full cost of wildfires. Federal firefighting spending averaged over 1 billion dollar annually during our sample period and has been growing significantly in recent years, while annual firefighting spending by the state also amounts to hundreds of millions of dollars.[29] Other costs of wildfires not borne by municipalities include the health impacts of the smoke, habitat destruction, carbon emissions, and increased risk of landslides. Local governments, while making many of the key land use and building decisions that influence wildfire risk levels, do not shoulder many of these costs of wildfires, likely leading to sub-optimal levels of investment in risk management. In our analysis, we do find

[27] See, for example, CNBC's reporting on S&P Global Ratings (https://www.cnbc.com/2017/10/13/california-wildfire-disaster-could-bring-local-fiscal-pain-for-years.html), or Breckinridge Capital Advisors (https://www.breckinridge.com/insights/details/municipal-implications-of-the-california-wildfires/).

[28] Reference: Moody's, January 24, 2019 (https://www.moodys.com/research/Moodys-downgrades-California-Statewide-Communities-Development-Authority-Taxable-POBs-2007–PR_905682075).

[29] Reference: National Interagency Fire Center, "Federal Firefighting Costs (Suppression Only)", https://www.nifc.gov/fire-information/statistics/suppression-costs.

direct evidence of municipal governments increasing investments in public safety following the fire, which suggests they believe they had under-invested in such measures prior to the fire. Given the magnitude of wildfire costs that municipalities do not bear, however, this is likely to still be below economically optimal levels of risk mitigation. We believe understanding how local policies on land use and other risk-mitigation measures respond to wildfire events is an important area for future research.

Our findings also show that historic wildfires did not led to large population losses but rather a persistently higher level of spending on community development. While much of this spending is likely driven by rebuilding and recovery activities, it might also reflect efforts to enhance fire preparedness, or even a stronger demand for housing that propels rebuilding and continuing expansion of WUI (Mann et al., 2014). Past studies have shown that disasters might not generate harmful long-term effects and can sometimes lead to a renewal of outdated infrastructure and properties through a creative destruction mechanism (Davis and Weinstein, 2002; Siodla, 2015; Kocornik-Mina et al., 2020). Further research is needed to understand the necessary conditions for uniting wildfire recovery with risk reduction.

As wildfire risk escalates in California due to climate changes, our findings highlight an often overlooked cost of natural disasters: impacts on municipal finance. Changes in municipal expenditures and revenues can trigger changes in tax assessments and also have impacts on service delivery, both with welfare impacts for residents. Further investigation of how changes in municipal budgets impact households and businesses in the community would be useful follow-on research.

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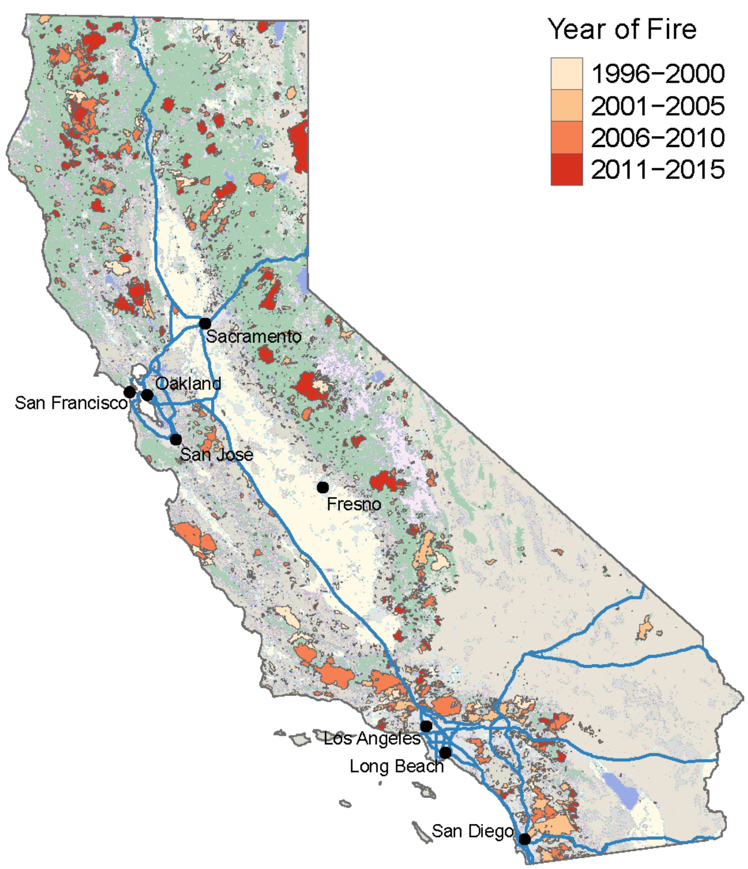
A Appendix Figures and Tables

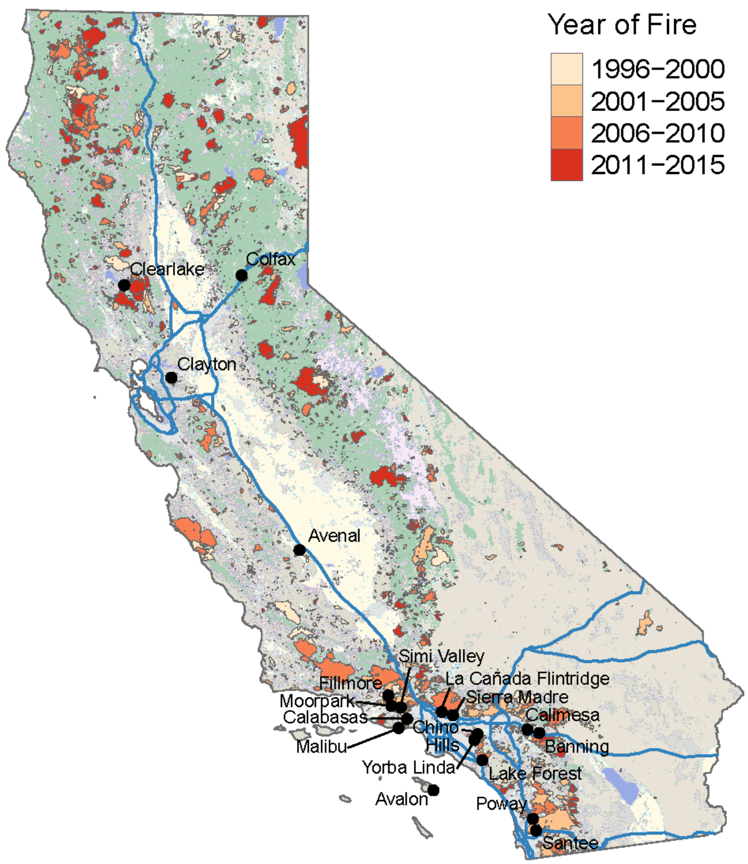
A.1 Figures

Figure A1: Fire perimeters, 1995-2015



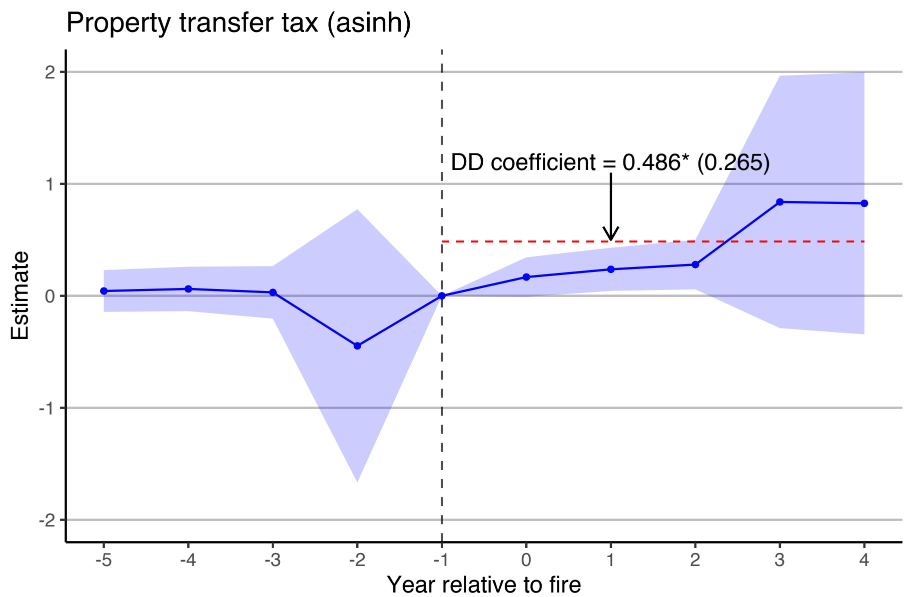
Notes: this map shows perimeters of all fires from FRAP. The four five-year periods (1996-2000, 2001-2005, 2006-2010, 2011-2015) are shown from light orange to red. The eight largest cities are marked in black and major interstate highways are shown in blue.

Figure A2: Exposed municipalities, 1995-2015



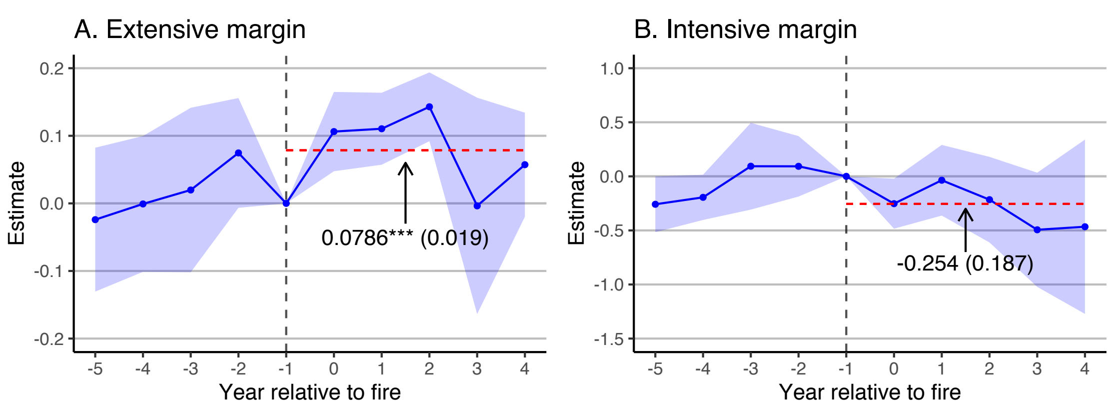
Notes: this map shows the municipalities that have been exposed to a major fire event during 1995-2015. Each exposed municipality is marked in black.

Figure A3: Wildfire impacts on property transfer tax revenues



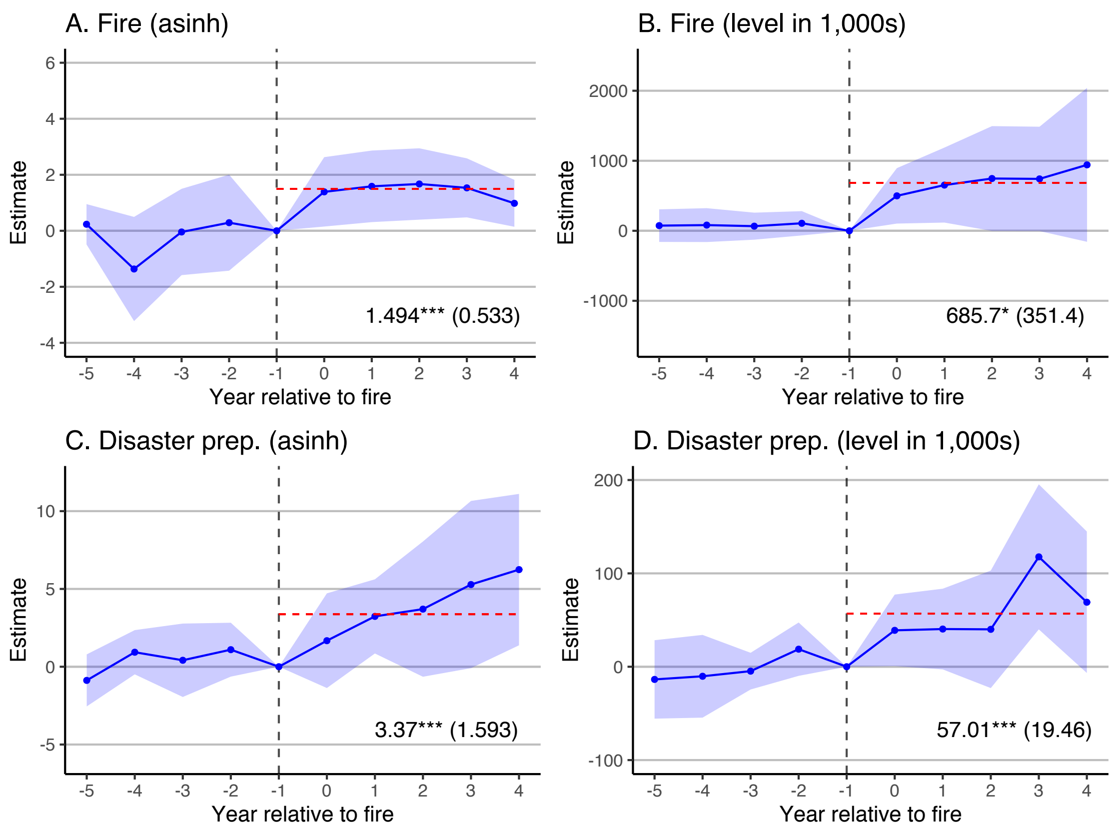
Notes: this figure shows point estimates from equation (1) and their 95% confidence intervals in blue, and the point estimate from equation (2) in red. The dependent variable is $asinh$-transformed revenues from property transfer tax. The implied change from the DD estimate is 56.97%. Statistical significance for the DD coefficient: *p<0.1; **p<0.05; ***p<0.01.

Figure A4: Decomposition of wildfire impacts on health expenditures



Notes: this figure shows point estimates from equation (1) and their 95% confidence intervals in blue, and the point estimate from equation (2) in red. Panel A is based on the full sample and the dependent variable is an indicator of recorded health expenditures being nonzero. Panel B is based on observations with positive recorded health expenditures and the dependent variable is the $asinh$-transformed health expenditures. The implied change from the DD estimate is 8.16% in Panel A; and -23.78% in Panel B. Statistical significance for the DD coefficient: *p<0.1; **p<0.05; ***p<0.01.

Figure A5: Wildfire impacts on fire and disaster preparedness expenditures



Notes: this figure shows point estimates from equation (1) and their 95% confidence intervals in blue, and the point estimates from equation (2) in red. The dependent variable is displayed at the top of each panel. The DD coefficient is displayed in the bottom left corner of each plot. Statistical significance for the DD coefficient: *p<0.1; **p<0.05; ***p<0.01.

A.2 Tables

Table A1: List of major wildfire incidents, 1995-2010

Calendar Year	City	% Pop. Exposed	% Area Exposed
1996	Calabasas	14.93	28.40
1996	Avenal	12.18	4.17
1998	Calimesa	23.79	12.94
2001	Colfax	17.08	0.00
2003	Fillmore	49.47	7.61
2003	Moorpark	21.97	31.28
2003	Simi Valley	14.69	17.47
2003	Santee	11.79	20.41
2003	Poway	10.46	27.89
2006	Banning	13.59	2.32
2007	Avalon	20.44	16.75
2007	Malibu	15.38	23.96
2007	Lake Forest	11.45	17.60
2008	Yorba Linda	30.35	38.89
2008	Chino Hills	13.30	42.46
2008	Sierra Madre	11.05	17.82
2009	La Canada Flintridge	15.50	16.83

Notes: this table lists all instances of a wildfire affecting more than 10% of the population in a municipality between 1995 and 2010. The four columns show the calendar year, the city, percent of population exposed, and percent of land areas exposed.

Table A2: Municipal budget - revenues

Category	Descriptions
Taxes$^{G, F}$	Property taxes, interest, penalties, and delinquent taxes, sales and use taxes, transportation tax, transient lodging taxes, franchises, business license taxes, real property transfer taxes, utility users taxes, construction development taxes, transportation tax, and other non-property taxes
Licenses and Permits$^{G, F}$	Animal licenses, bicycle licenses, construction permits, streets and curb permits, and others
Fines and Forfeitures$^{G, F}$	Vehicle code fines, other fines, forfeitures and penalties
Use of Money and Property$^{G, F}$	Investment earnings, rents and concessions, royalties, and others
Intergovernmental Transfers	
Federal$^{G, F}$	Community development block grant, Workforce Investment Act (W.I.A.), other federal grants
State$^{G, F}$	Homeowners property tax relief, gasoline tax, peace officers standards and trainings, other state grants, mandated costs
County$^{G, F}$	County grants of state gasoline tax, and other county grants
Current Charges^{F}	Zoning fees and subdivision fees, special police department services, special fire department services, plan checking fees, animal shelter fees and charges, sewer service charges and connection fees, engineering fees, inspections, street, sidewalk, and curb repairs, solid waste revenues, weed and lot cleaning, water service charges, and many others (almost every service has a corresponding charge)
Others$^{G, F}$	Sales of real and personal property, contributions from non-governmental sources, welfare repayments, cancelled warrants, and others

^{G}: general revenues; ^{F}: functional revenues.

Table A3: Municipal budget - expenditures

Category	Descriptions
A. Breakdown by Activity	
General Government	Legislative, management and support
Public Safety	Police, fire, emergency medical service, animal regulation, weed abatement, street lighting, disaster preparedness, other
Transportation	Streets/highways/storm drains, street trees/landscaping, parking facility, public transit, airports, ports and harbors, other
Community Development	Planning, construction and engineering regulation enforcement, redevelopment, housing, employment, community promotion, other
Culture and Leisure	Parks and recreation, marina and wharfs, libraries, museums, golf courses, sports arenas and stadiums, community centers and auditoriums, other
Health	Physical and mental health, solid waste, sewers, cemeteries, other
Public Utilities	Water, gas, electricity, other
B. Breakdown by Nature of Spending	
Operating Expenditures	Include expenditures for operating leases, salaries and wages, retirement and other employee benefit contributions, contracted services with private or governmental agencies, and materials and supplies.
Capital Outlay	All expenditures for capital outlay from grants, bond proceeds, and any other revenue source.
Debt Service	Payments of interest and principal on all bonded indebtedness, long-term indebtedness, and lease obligations.

Table A4: Summary statistics - full panel

	Cities with fire exposure			Cities without fire exposure		
Statistic	N	Mean	St. Dev.	N	Mean	St. Dev.
Population	486	31,742.2	29,414.1	11,750	59,866.1	195,444.6
General revenues:						
Total	486	439.4	337.4	11,750	1,337.1	13,454.8
Taxes	486	372.4	329.1	11,750	918.5	7,443.2
Property tax	486	103.7	99.8	11,750	168.3	980.7
Sales and use tax	486	98.1	77.9	11,741	337.9	2,786.0
Property transfer tax	478	6.0	8.3	11,361	9.2	47.7
Functional revenues:						
Total	486	706.1	737.7	11,750	4,066.1	70,016.5
Taxes	486	45.1	53.0	11,750	128.9	2,539.9
Charges	486	373.8	532.6	11,741	3,105.2	58,848.1
Intergov. transfers	486	111.6	153.8	11,750	154.0	634.5
Expenditures:						
Total	486	1,089.2	948.7	11,750	5,211.7	87,506.1
Public safety	486	239.2	167.9	11,750	798.3	8,999.0
General government	486	149.8	158.3	11,750	412.7	5,354.0
Community dev.	486	127.0	208.5	11,750	360.3	4,461.4
Transportation	486	227.3	357.2	11,750	288.2	1,840.4
Culture and leisure	486	84.3	119.2	11,750	155.2	1,008.7
Health	486	146.1	337.3	11,750	219.1	1,207.8
Public utilities	486	111.1	254.6	11,750	2,958.5	70,801.2
Fire	486	46.9	96.6	11,749	303.0	4,732.1
Disaster	486	1.6	8.3	11,747	5.5	98.6
Excess func. revenues	486	−383.1	428.3	11,750	−1,145.7	39,169.4
Excess total revenues	486	56.3	290.4	11,750	191.4	37,234.6
Budget deficit	488	34.0%	-	11,754	38.0%	-
Charter city	488	2.9%	-	11,752	23.0%	-
Service category:						
A	488	4.7%	-	11,754	25.2%	-
B	488	37.3%	-	11,754	36.7%	-
C	488	0.0%	-	11,754	2.6%	-
D	488	31.6%	-	11,754	26.3%	-
E	488	21.1%	-	11,754	4.6%	-
F	488	5.3%	-	11,754	4.1%	-
X	488	0.0%	-	11,754	0.4%	-

Notes: all budget items are reported in dollars per capita. San Francisco is excluded from these statistics.

Table A5: DD Estimates on home buyer demographics

	Dependent variable:				
	$asinh$(Income)	%White	%Hispanic	%Black	%Occup
	(1)	(2)	(3)	(4)	(5)
Fire × Post	0.008	−2.711	2.795**	0.422	−0.226
	(0.024)	(1.720)	(1.009)	(0.414)	(0.425)
D.V. mean	-	67.8	10.5	1.63	90.2
Observations	1,151	1,151	1,151	1,151	1,151
R^2	0.968	0.970	0.925	0.705	0.891
Municipal FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: this table shows estimates from equation (2). Each column features a demographic variable displayed at the top, which are calculated based on mortgage data from the Home Mortgage Disclosure Act. These regressions are weighted by the number of records used to calculate the outcome variables. Standard errors are clustered by fire incident. *p<0.1; **p<0.05; ***p<0.01

Table A6: DD estimates on general revenue categories

	Dependent variable (asinh):			
General Revenues	Total	Taxes	Property Tax	Sales Tax
	(1)	(2)	(3)	(4)
Fire × Post	0.100***	0.105**	0.194***	0.097*
	(0.033)	(0.041)	(0.062)	(0.053)
%Change	10.5	11.0	21.2	10.0
Observations	1,169	1,169	1,169	1,169
R^2	0.980	0.975	0.734	0.970
Municipal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: this table shows estimates from equation (2). Each column features a general revenue category displayed at the top. The implied percent changes are reported below the estimates. Standard errors are clustered by fire incident. *p<0.1; **p<0.05; ***p<0.01.

Table A7: DD estimates on functional revenue categories

	Dependent variable (asinh):			
Functional Revenues	Total	Taxes	Service Charges	Intergov. Transfers
	(1)	(2)	(3)	(4)
Fire × Post	0.121*	1.260***	0.038	−0.039
	(0.073)	(0.486)	(0.158)	(0.092)
%Change	12.6	213.3	2.6	−4.2
Observations	1,169	1,169	1,169	1,169
R^2	0.916	0.572	0.898	0.727
Municipal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: this table shows estimates from equation (2). Each column features a functional revenue category displayed at the top. The implied percent changes are reported below the estimates. Standard errors are clustered by fire incident. *p<0.1; **p<0.05; ***p<0.01.

Table A8: DD estimates on expenditures by activity category

	Dependent variable (asinh):			
Expenditures	Total	Public Safety	General Government	Community Development
	(1)	(2)	(3)	(4)
Fire × Post	0.163***	0.171***	0.082	0.346**
	(0.035)	(0.049)	(0.068)	(0.140)
%Change	17.6	18.5	8.3	40.0
Observations	1,169	1,169	1,169	1,166
R^2	0.957	0.910	0.852	0.783
	Transportation	Culture and Leisure	Health	Public Utilities
	(5)	(6)	(7)	(8)
Fire × Post	0.169*	−0.133	1.102***	0.194
	(0.098)	(0.171)	(0.263)	(0.119)
%Change	17.8	−13.7	190.8	20.6
Observations	1,169	1,169	1,169	1,169
R^2	0.850	0.599	0.871	0.983
Municipal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: this table shows estimates from equation (2). Each column features a major expenditure category displayed at the top. See Table A3 for a detailed description of these activity categories. The implied percent changes are displayed below the estimates. Standard errors are clustered by fire incident. *p<0.1; **p<0.05; ***p<0.01

Table A9: DD estimates on fire and disaster preparedness expenditures

	Dependent variable:			
	Fire		Disaster Preparedness	
	asinh	level (1,000s)	asinh	level (1,000s)
	(1)	(2)	(3)	(4)
Fire × Post	1.494***	685.736*	3.370**	57.008***
	(0.533)	(351.357)	(1.593)	(19.457)
%Change	286	75.5	721	164
D.V. mean	6.74	908.6	4.45	34.77
Observations	1,169	1,169	762	762
R^2	0.915	0.872	0.684	0.321
Municipal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: this table shows estimates from equation (2). Columns (1) and (2) feature expenditures on fire in *asinh*-transformation and levels (in 1,000s). Columns (3) and (4) feature the same for expenditures on disaster preparedness. The implied percent changes are displayed below the estimates. Standard errors are clustered by fire incident. *p<0.1; **p<0.05; ***p<0.01

Table A10: DD estimates on budget balance

	Dependent variable:	
	Per Capita Functional Revenues in Excess of Expenditures	Per Capita Total Revenues in Excess of Expenditures
	(1)	(2)
Fire × Post	-167.883^{***}	-97.101^{***}
	(45.297)	(34.672)
D.V. mean	−296.9	47.58
Observations	1,169	1,169
R^2	0.751	0.252
Municipal FE	Yes	Yes
Year FE	Yes	Yes

Notes: this table shows estimates from equation (2). The dependent variable is per capita functional revenues in excess of expenditures in columns (1) and per capita total revenues in excess of expenditures in columns (2). Standard errors are clustered by fire incident. *p<0.1; **p<0.05; ***p<0.01.

Table A11: Robustness check with incident fixed effects

	Dependent variable (asinh):				
	Population	General Revenues	Functional Revenues	Total Expend.	Total Excess Revenues
	(1)	(2)	(3)	(4)	(5)
Fire × Post	-0.008	0.100^{***}	0.121	0.161^{***}	-92.373^{**}
	(0.012)	(0.033)	(0.072)	(0.035)	(33.665)
%Change	-0.80	10.5	12.6	17.4	-
Observations	1,169	1,169	1,169	1,169	1,169
R^2	0.998	0.980	0.917	0.958	0.259
Municipal FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Incident FE	Yes	Yes	Yes	Yes	Yes

Notes: this table shows estimates on major outcomes from equation (2) but with additional incident fixed effects. Columns (1)-(4) feature $asinh$-transformed outcomes displayed at the top. The implied percent changes are reported below the estimates. The outcome in column (5) is per capita total excess revenues. Standard errors are clustered by fire incident. *p<0.1; **p<0.05; ***p<0.01

Table A12: Robustness check with population weights

	Dependent variable:				
	Population	General Revenues	Functional Revenues	Total Expend.	Total Excess Revenues
	(1)	(2)	(3)	(4)	(5)
Fire × Post	−0.007	0.100***	0.103*	0.164***	−81.837***
	(0.010)	(0.028)	(0.056)	(0.022)	(25.579)
%Change	−0.70	10.4	10.8	17.8	-
Observations	1,169	1,169	1,169	1,169	1,169
R^2	0.998	0.987	0.918	0.964	0.283
Municipal FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: this table shows estimates on major outcomes from equation (2) but weighted by population of the exposed cities in the year prior to the fire. Columns (1)-(4) feature $asinh$-transformed outcomes displayed at the top. The implied percent changes are reported below the estimates. The outcome in column (5) is per capita total excess revenues. Standard errors are clustered by fire incident. *p<0.1; **p<0.05; ***p<0.01

Table A13: Robustness checks with alternative fire event definition

	Dependent variable:				
	Population	General Revenues	Functional Revenues	Total Expend.	Total Excess Revenues
	(1)	(2)	(3)	(4)	(5)
Fire × Post	−0.016	0.066*	0.139***	0.139**	−11.537
	(0.019)	(0.038)	(0.054)	(0.054)	(50.274)
%Change	−1.6	6.7	14.8	14.7	-
Observations	709	709	709	709	709
R^2	0.999	0.995	0.988	0.992	0.250
Municipal FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: this table shows estimates from an alternative wildfire event measure, defined based on the total number of people affected. Columns 1-4 feature $asinh$-transformed outcomes displayed at the top. The implied percent changes are reported below the estimates. The outcome in column (5) is per capita total excess revenues. Standard errors are clustered by fire incident. *p<0.1; **p<0.05; ***p<0.01

Table A14: Heterogeneous effects by wildfire severity

	Dependent variable:				
	Population	General Revenues	Functional Revenues	Total Expend.	Total Excess Revenues
	(1)	(2)	(3)	(4)	(5)
Severe Fire × Post	-0.004	0.103	0.001	0.095^{**}	-166.418^{*}
	(0.010)	(0.083)	(0.071)	(0.041)	(84.293)
Other Fire × Post	-0.009	0.099^{***}	0.172^{*}	0.192^{***}	-61.186^{*}
	(0.018)	(0.031)	(0.096)	(0.050)	(30.144)
%Change - Severe	-0.40	10.5	-0.15	9.9	-
%Change - Other	-0.91	10.4	18.2	21.0	-
Observations	1,169	1,169	1,169	1,169	1,169
R^2	0.998	0.980	0.916	0.957	0.264
Municipal FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: this table shows separate estimates on major outcomes for fires with over 20% population exposure (Severe Fire) and those with 10-20% population exposure (Other Fire). Columns (1)-(4) feature $asinh$-transformed outcomes displayed at the top. The implied percent changes are reported below the estimates. The outcome in column (5) is per capita total excess revenues. Standard errors are clustered by fire incident. *p<0.1; **p<0.05; ***p<0.01