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 and property taxes increase to a permanently higher level; this appears due to 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, municipalities are surprisingly insulated from the costs of wildfires.

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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. In particular, maintaining fiscal soundness is crucial for local governments to consistently deliver the desired level of public services to residents. If a disaster impedes a local government's ability to maintain a balanced budget, this will entail greater borrowing and higher taxes down the road and ultimately lead to negative welfare consequences for residents. And 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] These studies include Stetler et al. (2010), Mueller and Loomis (2014), McCoy and Walsh (2018), Garnache and Guilfoos (2019).

they bear little of the wildfire suppression 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 (SCO), contains a breakdown of municipal budget categories for both revenues and expenditures. The ability to track expenditures across categories and revenues across sources 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 the 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 than those that never experience wildfire, most notably in size. As such, we construct our control group to be municipalities that experience a wildfire at least once in our time period. We are thus comparing municipalities that are exposed to ones that will be exposed earlier or later. 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 a determination of the different channels of fiscal impacts on local governments, which then 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 public safety and community development, rather than a one-time response, suggesting that economic recovery from disasters necessitated extra spending from municipalities spanning multiple years. 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 and radically less than the suppression cost incurred at the federal level.

The overall impacts on municipal budgets, however, 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 precautionary tale for future severe wildfires or wildfire-prone places in other states, where some of these favorable elements might not exist.[3] Indeed, we find additional evidence that the more severe wildfires have led to much more negative impacts on budget balance.

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) 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). Two papers look at more detailed budget impacts of disasters, but one focuses on transfers to individuals (Deryugina, 2017) and the other on state governments (Miao et al., 2018). In this paper, we provide novel estimates of budgetary impacts of natural disasters 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

[3]For instance, 90% of the population left the town of Paradise after the entire town burned down in the 2018 Camp Fire. Home insurers have also started charging much higher premiums or dropping out from high-risk zip codes altogether.

[4]Cases studies on local governments have not changed their land use practices in response to a fire

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 wildfire suppression (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 that directly increases the demand on spending. 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. This is similar to the findings in Jerch (2018) regarding higher spending induced by federal mandates. 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

(Mockrin et al., 2018) or sea level rise risks (Shi and Varuzzo, 2020).

outlines a conceptual framework for interpreting the empirical results. Section 5 reports and discusses the results. Section 6 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).[5] 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 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

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

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 wildfire suppression 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. This is a relatively smaller wildfire 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 are costly and undesirable. 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 firefighting costs, their incentives to lower risk may be weaker (Baylis and Boomhower, 2019). That said, wildfires could still threaten a city's financial 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, electricity, and other utilities.

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 on them.

The same data also contains information on city characteristics, such as estimated population, service responsibilities[6], and its governing system[7], 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

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

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

rates to one percent and restricts annual increases in assessed property values to an inflation factor that cannot exceed 2 per cent 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 sold later.

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.[8] 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.[9] This yields a proxy of the 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".[10] An indicator of a major wildfire is less prone to measurement error than a measure of exposure intensity, and we will use it in our main analysis. There are 17 such incidents during 1995-2010.[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. As a robustness check,

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

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

[10]Note that a big wildfire might impact multiple municipalities at the same time, and we consider each a separate event.

[11]Fillmore, Malibu, and Moorpark experience more than one wildfire. We count the most significant one ranked by the population-based measure of wildfire exposure.

this alternative measure is constructed by directly overlaying the shapefiles of cities and fire perimeters to calculate the percent of land areas in a city that has been exposed to fires. The two measures show similar patterns of wildfire occurrences but different exposure extents.[12] As expected, the area-based measure is larger in most instances, suggesting the fires tend to affect areas with lower population density. While population exposure might capture more of the actual fire impacts than area exposure, the discrepancy between the two further supports using a binary measure in the analysis.

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.

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

[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.

[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).

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 experience a wildfire at a different 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 some other 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 un-

[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 matching, 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).

treated 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

$$Y_{iwt} = \sum \quad Fire_{iw} \times EventTime_{wt} + \quad Fire_{iw} + \quad_{i} + \quad_{t} + \varepsilon_{iwt}; \tag{1}$$

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 zero- and even negative-valued observations, which is common among municipal budget items.[16] $Fire_{iw}$ equals one if i is the exposed municipality in event w, and zero otherwise. $EventTime_{wt}$ 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 goes from -5 to 4 so that we observe five years each in the pre- and post-fire periods. Lastly, $_{i}$ denotes a municipal fixed effect, which controls for time-invariant municipal characteristics of finances, geography, and underlying wildfire risks. $_{t}$ 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.

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

The ’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 when the treatment effect changes over time (e.g. Goodman-Bacon, 2018; Callaway and Sant’Anna, 2019). The problem arises when later treated units are compared with earlier treated units in their post period, which 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. Our estimates are thus not contaminated by such problematic comparisons.

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

$$Y_{iwt} = \quad Fire_{iw} \times Post_{wt} + \quad Fire_{iw} + \quad_{i} + \quad_{t} + "_{iwt}; \tag{2}$$

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. 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 Conceptual Framework

Wildfires can have varying economic impacts, which could lead to different budgetary adjustments. This complicates the welfare interpretation of any single revenue or expenditure adjustment we might observe in the data. In this section, we outline a conceptual framework on the connection between the various budgetary adjustments and household welfare (see Appendix B for the formal model). The key finding is that the existence and magnitude of any budget deficit during the recovery can be a reliable indicator of the direction and magnitude of the welfare change.

The model considers a community of population n in two periods, that experiences a wildfire at the beginning of period 1. We interpret period 1 as the years immediately following the wildfire when the community is recovering from the fire, which we observe in our data. Period 2 represents the later years when the local government seeks to recover from any budgetary disruptions in period 1. The community can borrow in period 1, but it has to repay the debt and have a balanced budget by the end of period 2. The representative household in the community earns income Y in each period and pays a tax to fund a public good. They derive utility from both private consumption (C) and the public good (S).

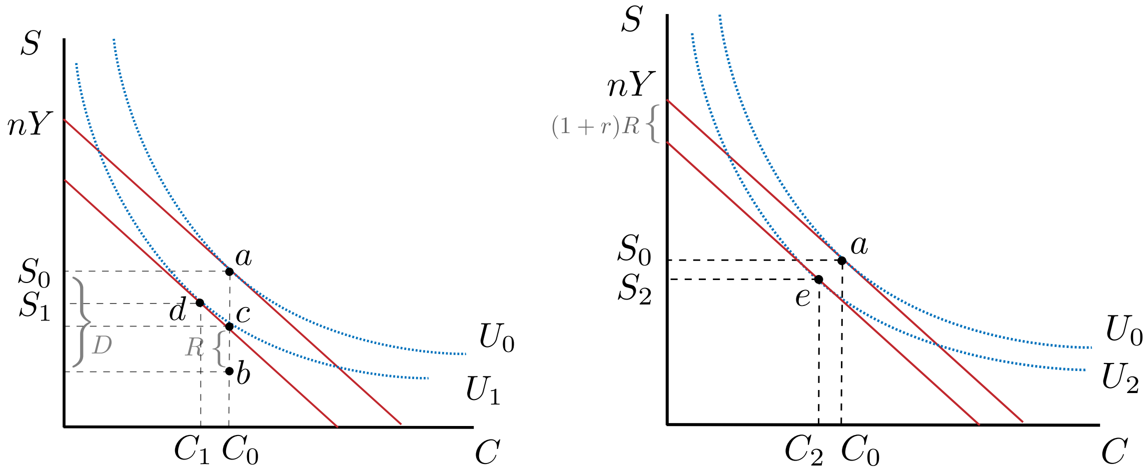
Absent the wildfire, the community is on a path with a balanced budget in each period and an optimal tax rate that maximizes resident welfare. In Figure 1, this consumption bundle is represented as point a, where the indifference curve (blue dotted curve) of utility level U_0 is tangent to the budget constraint (red solid line).

Now, suppose the community experiences a wildfire at the beginning of period 1. We consider two scenarios of its destructive effect: first, it destroys part of community public goods; second, it reduces the income level of households. Destruction of public goods could be, for example, damage to infrastructure or public buildings or a general decline in environmental quality caused by wildfire debris. Reduction in household income also captures the expenditure shock (and thus less net income) needed to pay for disaster repairs and reconstruction. For clarity, we discuss the scenarios separately.

Wildfire scenario 1. When the wildfire reduces the public good by an amount D, the community can restore part of the loss by increasing the tax rate and borrowing an amount R. Graphically, these fiscal adjustments in period 1 are represented in panel (a) of Figure 1. The initial drop in public good level moves the consumption bundle from point a to b. To recover, the community then borrows R to increase the budget to the level of bundle c, and further raises taxes to move to the optimal bundle d under this new budget. In period 2 as shown in panel (b), the budget constraint will adjust downward by $(1 + r)R$ as the community needs to repay its debt and interest, shifting the consumption bundle from point a to e.

In this setting, we see an increase in both expenditure and revenue of the local government in period 1, but overall social welfare decreases. Formally, we further show that

Figure 1: Wildfire scenario 1 - reduction in public good



(a) Period 1

(b) Period 2

the welfare loss is directly proportional to the budget deficit R during the recovery (see Proposition 1 in Appendix B).

Wildfire scenario 2. Next, we consider the second scenario where the wildfire reduces the income of residents. Both the tax base and the household's disposable income decrease, leading to a smaller budget overall. In Figure 2, this is represented by a downward shift in the budget constraint from l_1 to l_3 in panel (a). Again, it is optimal for the government to borrow, shifting the budget constraint up to l_2, and adjust the tax rate to attain the optimal bundle at point f. Similarly, the need to balance the budget in period 2 lowers the budget by $(1 + r)R$, leading to the same change from bundle a to e in panel (b).

Here, in contrast to the previous scenario, both expenditure and revenue decrease in period 1. However, the overall welfare changes in the same direction and is again proportional to the deficit (see Proposition 2 in Appendix B).

In summary, we used a stylized model to explore two plausible scenarios of how a wildfire can affect the community. We find that changes in revenue and expenditure depend on the specific scenario, but the deficit consistently indicates both the direction and magnitude of the welfare change across scenarios. This is intuitive: the community uses debt (*i.e.* deficit) to mitigate the immediate damage of the wildfire and smooth consumption

Figure 2: Wild re scenario 2 - reduction in household income

(a) Period 1

(b) Period 2

across periods, and hence the increase in debt is commensurate with damage. Therefore, in our empirical analysis, we examine adjustments in budget sub-components to gain insights into the nature of immediate wild re damages, but ultimately rely on changes in the de cit to make inferences about welfare.

It should be noted that this framework does not account for insurance coverage, which could recover most of the damage in scenario 2. This framework also does not account for the possibility that the community might have under-invested in risk-reduction and preparedness measures in the rst place. In this case, the re might motivate the community to borrow and ramp up these efforts. Therefore, part of the de cit could represent productive investment that leads to an increase in subsequent welfare. In our empirical analysis, we examine budget categories that are speci cally related to risk-reduction and preparedness to gauge the extent of this third channel.

Figure 3: Wild re impacts on population

Notes: this gure shows point estimates from equation (1) and their 95% con dence intervals in blue, and the point estimate from equation (2) in red. The dependent variable is asinh-transformed population. Statistical signi cance for the DD coef cient: $p < 0.1$; $p < 0.05$; $p < 0.01$.

5 Results

5.1 Population

Natural disasters might induce migration responses. After a major re 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 scal changes are due to population changes in the municipality. We thus begin by estimating population changes in wild re-impacted municipalities.

Figure 3 plots the event study estimates from equation (1) and their 95% con dence intervals in blue. The outcome variable is population after asinh transformation. The vertical dashed line at -1 indicates the likely timing of the wild re incident, as the wild re season is usually at the beginning of the current scal 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 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, Californian households might have lower mobility than other parts of the country due to a longstanding shortage of housing supply and the lock-in effect of Proposition 13 (Wasi et al., 2005; Ferreira, 2010). Second, the population measure in Boustan et al. (2017) 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.

To sum up, we estimate a small and temporary decrease in municipal population following a major wildfire incident. The flat pre-trend in population strongly supports the validity of our research design. Any impacts we find in the subsequent analysis on municipal finance, therefore, are not likely due to changes in population.[18]

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

[18] One caveat is that we do not have the necessary data to examine whether there are demographic shifts, which is possible as a result of the increase in home sales we observe below. Even if this is the case, however, sorting is not a likely explanation for our subsequent results on budget changes since it is only a small percent of total homes that transacted across multiple years post-fire. The preferences of the new residents would

5.2 Revenues

We start with general revenues. Figure 4 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 A5. All four panels show a relatively at 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 re. 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 ve 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 in property tax revenues averaging 21.2% over ve years, and an increase in sales tax of 10%.

The results for property values may initially appear surprising. Prior work has found housing values can decline post-disaster, although price effects from wild res have been found to be short-lived (McCoy and Walsh, 2018; Garnache and Guilfoos, 2019). There are a couple possible explanations for our ndings given that we found in Section 4.1 that post-wild re population changes were minimal. It is possible that some areas impacted by wild re do lose value, but other safer areas in the same municipality gain in value. For example, areas with higher structure density are safer from re 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 well covered by insurance. This, in turn, leads to an increase in home values. We nd it most likely, however, that the explanation of our result comes from Proposition 13.

As noted above, Proposition 13 arti cially suppresses property assessments in California until the time of sale. As such, turnover in property often leads to higher property taxes. If the wild re increases transaction volumes, it could generate higher property taxes for the municipality through this mechanism.[18] Note, that even if the wild re led to some

not manifest in immediate budget changes, such as we are observing below.

[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.

Figure 4: Wild re impacts on general revenues

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

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-wild re transactions. In Colorado, McCoy and Walsh (2018) has found that home transactions increase as the housing market adjusts after a re. While we do not have housing transactions data, 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 nd a large relative increase of 57% in

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

the ve years following the re (Figure A3). In particular, the dynamics match those of property tax revenues – an immediate increase followed by a second increase in event year 3 – which provides strong evidence that the change in property tax revenues is related to higher transaction volumes.

Sales taxes also increase after the wild re. This is likely due to increased spending on rebuilding. Homeowners insurance, which covers wild re 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 re, 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).

Next, we examine functional revenues. Figure 5 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 A6. In Panel A, the point estimates indicate a 7% drop in functional revenues in the year of the re, 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,

[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/ re-department-parcel-tax-increase-ballot).

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

Figure 5: 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.

we examine whether city governments are incurring higher costs that may justify these tax increases.

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.

5.3 Expenditures

In this section, we examine expenditures for different service activities. Figure 6 plots the event study estimates on expenditures in total and by major activity category. The corresponding DD estimates are reported in Table A7.

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. 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 and 40% for community development. Both categories contain spending on activities that are highly relevant for post-disaster response, a point we will explore further below. 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 plausible 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 for 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. Finally, 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 the "extensive" (whether the observation is nonzero) and "intensive" (estimation based on

[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 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.

Figure 6: Wild re impacts on expenditures

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

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 public safety and community development 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 activities post-fire, most likely a range of spending to help rebuild the economy and public goods of the community. Second, there could be an increase in disaster preparedness efforts motivated by the salience of wildfires. This aligns with one prior study, which found that in eight locations across the U.S., communities increased wildfire suppression, emergency response, and hazard planning documents following a wildfire (Mockrin et al., 2018). Next, we will examine this further in our data.

Specifically, we focus on two groups of activities 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. Because both are small expenditure categories with many zero observations, results based on *asinh*-transformation might not be reliable (Bellemare and 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 in fire and disaster preparedness expenditures. The corresponding DD estimates and implied percent changes are reported in Table A8. We first examine spending on fire. Panel A shows a clear and persistent increase in the *asinh*-transformed total fire expenditures, with the magnitude of a 287% increase from the pre-fire level (column (1), Table A8). The estimates in panel B also support this qualitative pattern but show a much smaller relative increase at 75.5%. In terms of 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 a 164% increase.

The discrepancies in the implied percent change across estimates within the same category substantiate our concern regarding the asinh-transformation. We thus caution against taking these magnitudes literally. Moreover, since fire and disaster preparedness only account for 4.3% and 0.15% of the overall expenditure, respectively, they are not likely to be a major driving force of the overall 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 fire suppression 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 public safety, community development, and transportation. We find no evidence that the increase in these categories crowds out other spending. Community development represents the largest increase, and this is likely 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.

5.4 Budget Balance

In the previous two sections, we find that wildfires lead to both higher revenues and higher expenditures. As shown in Section 4, the ultimate indicator of the direction and size of the welfare impacts is the overall budget balance. If higher revenues make up for the increased demand on spending, then the municipality can remain in good financial health despite the fire. If, instead, the municipality runs a deficit, then it would have negative welfare consequences. 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 7, and the corresponding DD estimates are reported in Table A9. 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 7: Wild re impacts on budget balance

Notes:this gure shows point estimates from equation (1) and their 95% con dence 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.

but not overwhelming.

We also examine the probability of having an overall budget de cit, that is, when excess revenues are negative (Figure 8). Not surprisingly, we nd a higher probability of having a budget de cit following the re. The average increase over ve 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 wild res increase budget challenges for municipal governments. Both the decrease in excess revenues (increase in de ciency) and the increase in the probability of a budget de cit are substantial. A small part of this effect could be attributed to increased investment in re preparedness, which might be welfare-improving. However, this effect is largely driven by rebuilding activities, which is similar to scenario 1 in our conceptual framework and implies signi cant welfare loss.

5.5 Additional Analyses

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

Figure 8: Wild re impacts on the probability of overall de cit

Notes: this gure shows point estimates from equation (1) and their 95% con- dence intervals in blue, and the point estimate from equation (2) in red. The dependent variable is an indicator of having an overall budget de cit. Statistical signi cance for the DD coef cient: $p < 0.1$; $p < 0.05$; $p < 0.01$.

Incident xed effects. By construction, a later-exposed city can appear in the sample 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 speci cation with an additional incident xed effect. Table A10 reports the DD estimates on ve 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 actually falls short of this goal, comparing weighted and unweighted estimates is useful for gauging the extent of mis-speci cation in the model (Solon et al., 2015). Recall that our sample consists of incident-speci c sub-samples. We weigh all observations in each sub-sample by the population of the exposed city one year prior to the incident. Table A11 reports the DD estimates on the same ve outcomes as above. Again, the estimates are quite similar to our main results.

Heterogeneous severity So far in this paper, we have focused on a binary measure of major wild re incident. However, there might be non-linear relationships between some outcomes of interest and the re severity. For example, we nd an increase in property tax revenues driven by an increase in transactions. A more severe re, however, may not further increase these revenues as the destructive effects of the re ramp up. Therefore, it is interesting to examine heterogeneous effects for incidents of different severity. We do so by splitting the DD indicator in equation (2) into two groups, one indicating the ve res that have a population exposure over 20% (“severe re” below), and the other indicating the twelve res with 10-20% population exposure (“other re” below). Table A12 reports estimates from the same set of major outcomes as above. We nd similar estimates for the two sets of res on population and general revenues. In particular, the estimate on general revenues for severe res is noisy and statistically insigni cant, but the magnitude is very similar to the other res. This suggests that the mechanism of Proposition 13 is also likely at play, though not further ampli ed to create more positive effects. We do, however, nd a marked difference between the severe res and others in the remaining outcomes. The severe res are not associated with any increase in functional revenues. Moreover, the increase in expenditures following a severe re is half the effect of other res. Together, these results suggest that cities affected by a severe re might have more dif culties nancing the extra spending needs induced by re. Indeed, severe res 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 res compared to $61 following the other res.

6 Conclusion

In this paper we investigate the impact of wild res on municipal revenues and expenditures. The wild res 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 wild- res and provide a lower bound on impacts from more severe res. We nd that historical wildfires during 1991-2010 increase both revenues and expenditures in certain categories, but the overall impacts on a municipality's budget are negative and worse for more severe fires. This suggests that even modest wildfires can be fiscally harmful to local governments. This may be even more pronounced outside of California, since one of the main sources of increased post-wildfire revenues in California 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 little change in the demand for housing in these municipalities. 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 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 a wildfire through functional taxes for more moderate fires. 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. 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 wild res in California, which took a much more severe toll on a few municipalities.[28]

The ndings of this paper add to our understanding of the incentives of local governments to invest in re mitigation. On the one hand, we nd that wild res 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 wild res. State and federal re suppression spending can reach into the billions of dollars and has been growing signi cantly in recent years. Other costs of wild res 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 in uence wild re risk levels, do not shoulder many of these costs of wild res, likely leading to sub-optimal levels of investment in risk management. In our analysis, we do nd direct evidence of municipal governments increasing investments in public safety following the re, which suggests they believe they had under-invested in such measures prior to the re. Still, though, given the magnitude of wildifre costs that municipalities do not bear, this is likely to still be below economically optimal levels of risk mitigation. In addition, such disaster-driven policy responses may be inef cient (Anderson et al., 2018). While we also observe an increase in spending on community development, it is not clear whether it re ects longer-term rebuilding and recovery, an effort to enhance re preparedness, or simply a strong demand for housing that propels rebuilding and continuing expansion of WUI (Mann et al., 2014). We believe understanding how local land use policies respond to wild re events is an important area for future research.

As wild re risk escalates in California due to climate changes, our ndings highlight an often overlooked cost of natural disasters: impacts on municipal nance. Changes in municipal expenditures and revenues can trigger changes in tax assessments and also have

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

[28] Reference: Moody's, January 24, 2019 (https://www.moodys.com/research/Moodys-downgrades-California-Statewide-Communities-Development-Authority-Taxable-POBs-2007-05R82075).

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 res from FRAP. The four ve-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 re 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 wild re impacts on health expenditures

Notes: this gure shows point estimates from equation (1) and their 95% con dence 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 signi cance for the DD coef cient: $p < 0.1$; $p < 0.05$; $p < 0.01$.

Figure A5: Wild re impacts on re and disaster preparedness expenditures

Notes: this gure shows point estimates from equation (1) and their 95% con dence 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 coef cient is displayed in the bottom left corner of each plot. Statistical signi cance for the DD coef cient: $p< 0.1$; $p< 0.05$; $p< 0.01$.

A.2 Tables

Table A1: List of major wild re 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 wild re 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, re, 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 bene t 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 re exposure			Cities without re 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 de cit	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 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 re incident. $p<0.1$; $p<0.05$; $p<0.01$.

Table A6: 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 re incident. $p<0.1$; $p<0.05$; $p<0.01$.

Table A7: 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 re incident. $p<0.1$; $p<0.05$; $p<0.01$

Table A8: DD estimates on re 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 re 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 re incident $p < 0.1$; $p < 0.05$; $p < 0.01$

Table A9: 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 re incident. $p< 0.1$; $p< 0.05$; $p< 0.01$.

Table A10: Robustness check with incident xed effects

	Dependent variable:				
	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 xed 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 re incident. $p < 0.1$; $p < 0.05$; $p < 0.01$

Table A11: DD Estimates from Population-Weighted Regressions

	Dependent variable:				
	Population Revenues	General Revenues	Functional Expend.	Total Revenues	Total Excess
	(1)	(2)	(3)	(4)	(5)
Fire Post	0.007	0.099	0.104	0.164	81.889
	(0.010)	(0.028)	(0.056)	(0.022)	(25.639)
%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	0.284
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 re. 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 re incident. $p<0.1$; $p<0.05$; $p<0.01$

Table A12: Heterogeneous Effects Based on Wild re 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 res 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 re incident. $p<0.1$; $p<0.05$; $p<0.01$

B Theory Appendix

In this appendix, we provide the full model as outlined in Section 4. We first characterize a baseline scenario where no wildfire will occur, and then consider two scenarios of wildfire destruction.

Baseline

Consider a community of population n in two periods. The representative household in the community earns income Y in each period and pays τY in tax. The household derives utility from the consumption of a public good S and a numeraire good C. Their preference is represented by $U(S; C)$, which is increasing and globally concave. The public good is funded by tax revenues. The community can borrow and spend more on the public good in period 1, but it has to repay the debt and have a balanced budget by the end of period 2.

Absent the wildfire, the community is on a path with a balanced budget in each period and the tax rate is set to maximize resident welfare:

$$\begin{aligned} \max_{\tau} \quad & U(S; C) \\ s.t. \quad & C = (1 - \tau)Y; \quad S = n\tau Y \end{aligned} \tag{A1}$$

This yields the following first-order condition:

$$nU_S^{(0)} = U_C^{(0)}; \tag{A2}$$

where $U_S^{(0)}$ denotes the partial derivative of the utility function with respect to S and evaluated at the point $(S_0; C_0)$. The same also applies to $U_C^{(0)}$ and similar expressions later. We also combine the budget constraints into

$$S_0 = n(Y - C_0): \tag{A3}$$

The baseline consumption bundle is characterized by the two equations above.

Scenario 1: Impact on Public Good Level

Suppose the fire reduces the community's public good level by D. To prevent the large welfare loss from the sudden decrease in public goods, the local government can raise taxes and borrow to partly cover the damage. Its problem is given by the following:

$$
\begin{aligned}
\max_{\tau_1;\, \tau_2; R} \quad & U(S_1; C_1) + \beta U(S_2; C_2) \\
\text{s:t:} \quad & C_1 = (1-\tau_1)Y; \quad S_1 = n\tau_1 Y - D + R \\
& C_2 = (1-\tau_2)Y; \quad S_2 = n\tau_2 Y - (1+r)R
\end{aligned}
\tag{A4}
$$

Note The budget constraint for period 2 accounts for having to repay the debt with interest $(1+r)R$. The corresponding first-order conditions are the following:

$$
\begin{aligned}
nU_S^{(1)} &= U_C^{(1)} \\
nU_S^{(2)} &= U_C^{(2)} \\
U_S^{(1)} &= U_S^{(2)}
\end{aligned}
\tag{A5}
$$

The optimal consumption bundle is characterized by the above equations together with the combined budget constraint:

$$
(1+r)S_1 + S_2 = (1+r)n(Y - C_1) + n(Y - C_2) - D: \tag{A6}
$$

In this setting, we have the following proposition:

Proposition 1. The solution to the problem defined in (A4) satisfies the following conditions when compared to the baseline case defined in (A1): $\tau_1 = \tau_2 > \tau_0$, $R = D/(2+r)$, $C_1 = C_2 < C_0$, and $S_1 = S_2 < S_0$. The overall welfare change from the baseline is approximately $-U_S(S_0; C_0)D$.

Proof. Note that the first and second conditions in (A5) imply that the optimal consumption bundles in period 1 and 2 are on the same expansion path. Given the concavity of U, we must have $C_1 = C_2$ and $S_1 = S_2$, otherwise the third condition in (A5) will fail.

Next, we prove by contradiction that $C_1 < C_0$, $S_1 < S_0$. Suppose $C_1 \geq C_0$. If $S_1 < S_0$, then

$$
U_S^{(1)} > U_S^{(0)} = \frac{1}{n}U_C^{(0)} > \frac{1}{n}U_C^{(1)};
$$

where the both inequalities follow from the concavity of U. This contradicts the first condition of (A5). Therefore, we have $S_1 = S_2 \quad S_0$. However, if this is the case, then

$$
\begin{aligned}
(1+r)S_1 + S_2 \quad (1+r)S_0 + S_0 & \\
&= (1+r)n(Y \quad C_0) + n(Y \quad C_0) \\
&\quad (1+r)n(Y \quad C_1) + n(Y \quad C_2) \\
&> (1+r)n(Y \quad C_1) + n(Y \quad C_2) \quad D:
\end{aligned}
$$

This contradicts equation (A6). Therefore, $C_1 = C_2 < C_0$, $S_1 = S_2 < S_0$.

The result on the tax rates follow from above:

$$
\begin{aligned}
{}_2 = 1 \quad \frac{C_2}{Y} = 1 \quad \frac{C_1}{Y} = {}_1 \\
{}_1 = 1 \quad \frac{C_1}{Y} > 1 \quad \frac{C_0}{Y} = {}_0:
\end{aligned}
$$

Using the individual budget constraints on S_1 and S_2, we also have

$$
S_1 \quad S_2 = (n \ {}_1 Y \quad D + R) \quad (n \ {}_2 Y \quad (1+r)R) = (2+r)R \quad D = 0;
$$

which yields

$$
R = \frac{D}{2+r}:
$$

Finally, we calculate the approximate welfare change by taking a rst-order Taylor expansion around the original consumption point:

$$
\begin{aligned}
U_1 + \ U_2 \quad (1+ \ )U_0 = (1+ \ )(U_1 \quad U_0) & \\
&\quad (1+ \ ) \ U_C^{(0)}(C_1 \quad C_0) + U_S^{(0)}(S_1 \quad S_0)) \\
&= (1+ \ ) \ nU_S^{(0)}(C_1 \quad C_0) + U_S^{(0)}(S_1 \quad S_0) \\
&= (1+ \ )U_S^{(0)} \ nC_1 + S_1 \quad (nC_0 + S_0) \\
&= (1+ \ )U_S^{(0)}(nY \quad D + R \quad nY) \\
&= \quad U_S^{(0)} D
\end{aligned}
$$

□

From these ndings, we can see that tax revenue increases in both periods compared to the baseline, driven by the higher tax rate. Expenditure increases in period 1 because the community incurs extra spending to recover from the public good, but decreases in period 2 as the community repays its outstanding debt. The overall welfare loss takes an intuitive form as the product of the marginal utility from the public good and the public good damage in the wild re. Note also that it is directly proportional to the level of period 1 de cit R because it is proportional to the damage D.

Scenario 2: Impact on Income Level

Suppose the re reduces the resident's income level by L instead. In this case, both the public good and private consumption will decrease. To mitigate the negative welfare shock, the local government can borrow and smooth consumption over time. Its problem in this scenario is:

$$
\begin{aligned}
\max_{1;\ 2;R} \quad & U(S_1; C_1) + \ U(S_2; C_2) \\
s{:}t{:} \quad & C_1 = (1 \quad {}_1)(Y \quad L); \quad S_1 = n\ {}_1(Y \quad L) + R \\
& C_2 = (1 \quad {}_2)Y; \quad S_2 = n\ {}_2 Y \quad (1 + r)R
\end{aligned} \tag{A7}
$$

The corresponding rst-order conditions are the following:

$$
\begin{aligned}
nU_S^{(1)} &= U_C^{(1)} \\
nU_S^{(2)} &= U_C^{(2)} \\
U_S^{(1)} &= U_S^{(2)}
\end{aligned} \tag{A8}
$$

Again, the optimal bundle is characterized by the above conditions joint with the combined budget constraint:

$$
(1 + r)S_1 + S_2 = (1 + r)n(Y \quad L \quad C_1) + n(Y \quad C_2): \tag{A9}
$$

In this setting, we have the following proposition:

Proposition 2. The solution to the problem de ned in (A7) satis es the following conditions when compared to the baseline case de ned in (A1): ${}_2 > {}_0$, $R = nL{=}(2 + r)$, $C_1 = C_2 < C_0$, and $S_1 = S_2 < S_0$. In addition, the comparison of period 1 tax rate ${}_1$ and the baseline ${}_0$ is ambiguous, but the tax revenue is lower. The overall welfare change from the baseline is approximately $U_S(S_0; C_0) \quad nL$.

Proof. Notice the set of rst-order conditions are the same as before, which implies the community chooses the same bundle in each period: $C_1 = C_2$ and $S_1 = S_2$.

We show by contradiction that $C_1 < C_0$, $S_1 < S_0$. Suppose $C_1 > C_0$, then we must also have $S_1 \quad S_0$ so that the rst condition in (A8) can hold. But this contradicts with equation (A9):

$$
\begin{aligned}
(1+r)S_1 + S_2 \quad & (1+r)S_0 + S_0 \\
&= (1+r)n(Y \quad C_0) + n(Y \quad C_0) \\
&> (1+r)n(Y \quad L \quad C_1) + n(Y \quad C_2)
\end{aligned}
$$

Therefore, $C_1 = C_2 < C_0$ and $S_1 = S_2 < S_0$.

Using individual budget constraints, we can solve for the amount borrowed:

$$S_1 \quad S_2 = n(Y \quad L \quad C_1) + R \quad n(Y \quad C_2) + (1+r)R = 0$$

$$) \qquad R = \frac{nL}{2+r}$$

Period 2 tax rate is higher than the baseline and hence also the total revenue:

$$_2 = 1 \quad \frac{C_2}{Y} > 1 \quad \frac{C_0}{Y} = \quad _0:$$

Period 1 tax revenue is lower than the baseline:

$$n \ _1(Y \quad L) = S_1 \quad R < S_0 = n \ _0 Y:$$

Finally, we calculate the approximate welfare change by taking a rst-order Taylor expansion around the original consumption point:

$$
\begin{aligned}
U_1 + \ U_2 \quad (1 + \ )U_0 &= (1 + \ )(U_1 \quad U_0) \\
& (1 + \ ) \ U_C^{(0)}(C_1 \quad C_0) + U_S^{(0)}(S_1 \quad S_0) \\
&= (1 + \ )U_S^{(0)} \ n(Y \quad L) + R \quad nY \\
&= \quad U_S^{(0)} \quad nL:
\end{aligned}
$$

□

In this setting, tax revenue decreases relative to the baseline in the period 1 but increases in the next. Expenditure is lower than the baseline in both periods. The overall welfare loss takes a similar intuitive form and is also proportional to the level of period 1 de cit R.