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Salience and the Government Provision of Public Goods*

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Abstract

This paper examines how behavioral biases due to salient events can shape the government provision of public goods. We develop a theory in which competing communities lobby a government agency for allocations of a local public good. When one community's demand is biased due to the occurrence of a salient event, an inefficient allocation results. Our empirical application tests this theory using salient wildfire events and implementation of government projects to reduce wildfire risk. Although the occurrence of wildfire removes hazardous fuels and thus reduces risk to nearby communities, it may nonetheless increase community demands for fuels management projects due to biases induced by the salient wildfire event. We find evidence that communities experiencing recent nearby fires are subsequently more likely to receive fuels management projects, and use robustness checks to rule out competing explanations for this result. Our framework may also offer insights into government responses to terrorism, natural disasters, disease outbreaks, and environmental catastrophes.

Keywords: behavioral economics, public goods, salience, risk, public land management
JEL codes: D03 (Behavioral microeconomics: underlying principles), H41 (Public goods), Q24 (Land)

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1 Introduction

There are many reasons that governments may fail to provide the socially optimal amount of public goods, including rent seeking (Gradstein, 1993), tax competition (Bucovetsky *et al.*, 1998; Janeba and Wilson, 2011), political decision-making (Romer and Rosenthal, 1979; Barseghyan and Coate, 2014), and overlapping market areas (Hochman *et al.*, 1995), among others. This paper examines another obstacle to efficient provision: behavioral biases that can distort the public's demand for government-provided goods. In our framework, communities compete for a public good by lobbying the government. If the perceived value of the good is biased away from its true value, a community may lobby for and receive an inefficient level of the public good. Further, due to behavioral biases the perceived value of a public good can increase even when the benefits from the good have decreased. Thus, provision of the public good can increase even though the efficient quantity declined.

We consider the case in which demands for public goods are distorted by salient events.[1] Due to their emotional interest, concreteness, or temporal, spatial, and sensory proximity and visibility, salient events shape the ease with which information is brought to mind, which can influence or bias judgments (Taylor and Thompson, 1982; Nisbett and Ross, 1980; Tversky and Kahneman, 1973; Kahneman, 2003).[2] Empirical evidence from economics suggests that behavioral biases can affect human decision-making in the wake of salient events. For example, firm managers respond to local hurricanes by increasing corporate cash holdings (Dessaint and Matray, 2017) and house prices decrease following recent nearby floods or fires, especially if a burn scar from a fire is in the

[1]Here we use "salient" in its plain language meaning. In a later section, we more precisely document the many behavioral biases and heuristics that can arise from salient events.

[2]Some papers have defined salience more narrowly. For example, the definition Chetty *et al.* (2009) adopt focuses on visibility of information. Bordalo *et al.* (2012) define salient choices within a lottery to be those with unusually high or low pay-offs, which draw a decision-maker's attention. Our definition encompasses these definitions, and is consistent with the way the word "salience" is used within much of the related empirical literature (e.g., Dessaint and Matray, 2017; McCoy and Walsh, 2018; Bakkensen *et al.*, Forthcoming) and with its use colloquially.

house's line of sight (Bin and Landry, 2013; McCoy and Walsh, 2018).

In contrast to prior studies of the effect of behavioral biases on private good consumption, our main contribution is to show that behavioral biases can affect the provision of public goods. We start with a simple theory of public good provision with lobbying. In our model, the government allocates a local public good to two communities to maximize net benefits. Because the public does not bear the costs of the good, they have an incentive to lobby for more than the efficient amount. The government trades off the benefits from providing more of the public good against the opportunity costs and a penalty for not meeting the community's demand. An upward-biased perception of the good's value within a community can cause it to lobby more and receive an inefficient amount of the public good. Salient events can cause such biases, even when they also *decrease* the true value of the public good. When the value of a public good declines, the government will reduce the allocated quantity of the good and—absent behavioral biases—the public will reduce lobbying. However, if community members use heuristics like the availability or representativeness heuristic, their perceived value for the public good can go up, leading them to increase their lobbying effort. The result is that government provision of the public good can increase even when its value has declined.

We estimate the effects of salient events on public good provision by examining the distribution of government projects to reduce wildfire hazard.[3] These projects involve the removal of vegetation from public lands in order to reduce the severity of wildfires when they occur (Stephens *et al.*, 2009). We analyze whether fuels management projects are more likely to be placed near communities that have recently experienced a salient wildfire, proxied for by distance to the community. Both fuels treatments and wildfires reduce the severity of future fires by removing fuels from the landscape (Collins *et al.*, 2009). Thus, a close fire reduces the expected value of fuels management projects

[3]Fire hazard refers to the conditions on the landscape that affect fire behavior, including vegetation type and terrain. Fire risk is the probability that natural resources, structures, etc. are destroyed by wildfire.

in the same area. Yet our theory suggests that even where a recent fire has reduced risks to a community, it may lead the public to overestimate the benefits of fuels management and lobby for more fuels projects.[4] As a result, public agencies may inefficiently allocate fuels management projects to communities for which recent wildfire has already reduced risk.

We identify the effects of behavioral biases with a rich panel data set on all fuels management projects on federal forest lands in the western U.S. between 2003 and 2011. The dependent variable in our empirical model is a binary indicator for whether a fuels management project was implemented on a given plot of land (cell i) in year t. We focus on cells that are close to wildland-adjacent communities, which are potentially vulnerable to damages from wildfire. We think of wildland-adjacent communities as being "treated" by a salient event when a wildfire occurs close-by and we test how treatment changes the probability of fuels management near the treated community. We measure effects in the year of the fire and for several years following the fire. Our specification includes grid cell fixed effects to control for time-invariant determinants of fuels management decisions, such as fire hazard and proximity to assets at risk, and year-by-region fixed effects to control for time-trending unobservables that may be correlated with fire hazard, such as changes in fuel moisture content.

We find strong evidence that close fires increase the likelihood that fuels management projects will be placed near treated wildland-adjacent communities. The effect is relatively large but quickly attenuates, as would be expected if it is driven by recency or other short-lived behavioral biases. Our main results are robust to different definitions of "close" fires and projects, alternative ways of clustering standard errors, corrections for serial correlation, inclusion of placebo one- and two-year leads, and changes in the sample. An alternative explanation for our empirical results is that government agencies use the occurrence of wildfires to learn about risks from future fires, as in

[4] In our empirical application, we are unable to explicitly measure the change in risk due to a recent, nearby fire. Because a wildfire reduces flammable fuels, fire risk in the area near a wildfire can decline or remain the same, but cannot increase following a fire.

the application to flooding by Gallagher (2014). To rule out this explanation, our specification includes year-by-region effects for relatively small geographic regions. We expect that any time-varying correlates of fire hazard that might be revealed by the occurrence of a fire vary at broader geographic scales and will thus be captured by these time-varying effects. Further, we show that the effect of a nearby fire on the likelihood of a fuels management project does not vary with vegetation condition, as would be expected if the fire informed managers about the risk of future fires. We provide further support for the behavioral bias mechanism by showing that effects of close wildfires are magnified near communities with greater population and more housing units. Consistent with our theory, these tests suggest that close wildfires affect the residents of wildland-adjacent communities.

In the next section, we present the theoretical model. Section 3 illustrates how salient events can lead to behavioral biases that shape the benefits from a public good. Section 4 describes the context and the data used in the empirical application, and section 5 presents the main econometric specification and results, followed by a series of sensitivity analyses, robustness checks, and evaluation of learning as an alternative to behavioral biases. Conclusions are in the final section.

2 Theory

This section presents a model of public good provision with lobbying. The decision-maker is a government agency that provides a local public good to two identical communities $i = \{1, 2\}$. The cost of allocating Q_i units of the good to each community is $C(Q_1, Q_2) = \frac{1}{2}\eta(Q_1 + Q_2)^2$ and benefits from the public good are $B(Q_i) = \alpha_0 Q_i - \frac{1}{2}\alpha_1 Q_i^2$. The parameter α_0 plays an important role in the model. We allow for residents of the communities to have a perceived value of the parameter, $\tilde{\alpha}_0$, that may differ from its true value due to behavioral biases. This raises or lowers perceived marginal benefits, $\tilde{B}'(Q_i) = \tilde{\alpha}_0 - \alpha_1 Q_i$, for all values of Q_i. In contrast, the agency forms correct beliefs about α_0 and seeks to maximize the net benefits of providing the public good subject to a budget M. We assume that in the absence of lobbying, the agency allocates an efficient amount of the public good to each community, denoted Q_0^*, and that the total budget for the agency is set accordingly at $M = \frac{1}{2}\eta(2Q_0^*)^2$.[5]

Even if the agency allocates the efficient amount of the public good, members of a community have an incentive to lobby for more of it because they do not bear the costs of its provision. We assume the communities and the agency play separate leader-follower games in which each community lobbies for the good, taking into account the best response function of the agency.[6] Each community's lobbying cost is $C_{Li}(Q_{Li}) = \frac{1}{2}\lambda Q_{Li}^2$, where Q_{Li} is the *additional* amount of the good sought by the community beyond Q_0^*. One can think of Q_{Li} as being proportional to lobbying effort.[7] Community i finds the optimal Q_{Li} by solving:

$$\max_{Q_{Li}} \tilde{\alpha}_0(Q_0^* + Q_{Ai}(Q_{Li})) - \frac{1}{2}\alpha_1(Q_0^* + Q_{Ai}(Q_{Li}))^2 - \frac{1}{2}\lambda Q_{Li}^2 \tag{1}$$

In Equation (1), $Q_{Ai}(Q_{Li})$ is community i's conjecture about the additional amount of the public good it will obtain from seeking Q_{Li}. The optimal lobbying effort, Q_{Li}^*, is defined implicitly by:

$$(\tilde{\alpha}_0 - \alpha_1 Q_0^* - \alpha_1 Q_{Ai}(Q_{Li}^*))\frac{dQ_{Ai}}{dQ_{Li}} - \lambda Q_{Li}^* = 0 \tag{2}$$

Under lobbying, the agency incurs a cost of not meeting community i's demand, given by $\frac{1}{2}\gamma(Q_{Li}^* - Q_{Ai})^2$. The agency is the follower in the model and so has Cournot conjectures (i.e., it assumes that its choice of Q_{Ai} does not affect Q_{Li}^*, or $\frac{dQ_{Li}^*}{dQ_{Ai}} = 0$). Under lobbying, the agency

[5]The efficient provision Q_0^* is the solution to $\max_{Q_1,Q_2} \sum_i(\alpha_0 Q_i - \frac{1}{2}\alpha_1 Q_i^2) - \frac{1}{2}\eta(Q_1+Q_2)^2$, which yields $Q_0^* = \frac{\alpha_0}{(\alpha_1+2\eta)}$.

[6]Our model has the same structure as a Stackelberg industry. We make the communities the leaders in the games so that they conjecture that lobbying affects the provision of the public good.

[7]We express Q_{Li} in terms of units of the public good because it allows us to define the agency's loss function, below, in the same units.

maximizes the net benefits of providing more of the good, solving:

$$\max_{Q_{A1},Q_{A2}} \sum_{i=1}^{2}[\alpha_0(Q_0^* + Q_{Ai}) - \frac{1}{2}\alpha_1(Q_0^* + Q_{Ai})^2 - \frac{1}{2}\gamma(Q_{Li}^* - Q_{Ai})^2] - \frac{1}{2}\eta(2Q_0^* + Q_{A1} + Q_{A2})^2$$
$$\text{subject to} \quad \frac{1}{2}\eta(2Q_0^* + Q_{A1} + Q_{A2})^2 = M, \quad -Q_0^* \leq Q_{A1}, Q_{A2} \leq Q_0^* \tag{3}$$

The interior solution[8] to (3) satisfies:

$$\begin{aligned} \alpha_0 - \alpha_1(Q_0^* + Q_{A1}^*) - \gamma(Q_{L1}^* - Q_{A1}^*) &= 0 \\ \alpha_0 - \alpha_1(Q_0^* + Q_{A2}^*) - \gamma(Q_{L2}^* - Q_{A2}^*) &= 0 \\ Q_{A1}^* + Q_{A2}^* &= 0 \end{aligned} \tag{4}$$

The equations in (4) can be solved for the additional amounts of the public good provided to the communities:

$$\begin{aligned} Q_{A1}^* &= \frac{\gamma}{2(\gamma - \alpha_1)}(Q_{L1}^* - Q_{L2}^*) \\ Q_{A2}^* &= \frac{\gamma}{2(\gamma - \alpha_1)}(Q_{L2}^* - Q_{L1}^*) \end{aligned} \tag{5}$$

We assume that $\gamma - \alpha_1 > 0$ so that, all else constant, a community's lobbying effort increases public good provision. The equations in (5) imply that if the communities lobby the same amount, then each community receives the same quantity of the public good.

Using (5), we can define the conjectures made by the two communities. If each community takes the other community's lobbying effort as given (i.e., has Cournot conjectures), the conjecture in both communities is $\frac{dQ_{Ai}}{dQ_{Li}} = \frac{\gamma}{2(\gamma-\alpha_1)}$. Using this result with Equation (2), we obtain the amount

[8] The constraint on Q_{A1} and Q_{A2} ensures that negative quantities of the public good cannot be allocated.

of lobbying undertaken in each community as:

$$
\begin{aligned}
Q^*_{L1} &= K_0(\tilde{\alpha}_0 - \alpha_1 Q^*_0) + K_1 Q^*_{L2} \\
Q^*_{L2} &= K_0(\tilde{\alpha}_0 - \alpha_1 Q^*_0) + K_1 Q^*_{L1}
\end{aligned}
\tag{6}
$$

where $K_0 = \frac{4(\gamma-\alpha_1)^2}{4\lambda(\gamma-\alpha_1)^2+\alpha_1\gamma^2} > 0$ and $K_1 = \frac{\alpha_1\gamma^2}{4\lambda(\gamma-\alpha_1)^2+\alpha_1\gamma^2} > 0$. Because $K_1 < 1$, there is a stable Cournot equilibrium at $Q^*_{L1} = Q^*_{L2} = K_0(\tilde{\alpha}_0 - \alpha_1 Q^*_0)\frac{1+K_1}{1-K_1^2}$.[9] The equilibrium is symmetric when the two communities have the same beliefs about the benefits from the public good (i.e., they have the same perceived value of $\tilde{\alpha}_0$). In this case, the communities lobby the same amount and neither obtains more of the public good; rather, each community lobbies to prevent the other community from eroding their benefits. Moreover, when communities have true beliefs ($\tilde{\alpha}_0 = \alpha_0$), the efficient amount of the public good is allocated.[10]

In the empirical application, wildfires occur only near some communities and, thus, only a subset of them experience changes in the benefits of fuels management projects. We use the theoretical model to understand how public good provision changes when the benefits of the good change for community 1 but remain constant for community 2. Further, we consider separately changes in the benefit perceived by community 1 and the changes in the actual benefit to community 1 as understood by the agency. We evaluate the change in the total allocation to community 1, $Q^*_{01} + Q^*_{A1}$, due to changes in α_0 for community 1 ($d\tilde{\alpha}_{01}$ and $d\alpha_{01}$):

$$
d(Q^*_{01} + Q^*_{A1}) = \frac{\partial Q^*_{A1}}{\partial \tilde{\alpha}_{01}} d\tilde{\alpha}_{01} + \left(\frac{\partial Q^*_{01}}{\partial \alpha_{01}} + \frac{\partial Q^*_{A1}}{\partial \alpha_{01}} \right) d\alpha_{01} \tag{7}
$$

The budget constraint in Equation (3) implies an opposite change in the allocation to community

[9]The equilibrium lobbying amounts Q^*_{L1} and Q^*_{L2} are positive as long as $\tilde{\alpha}_0 - \alpha_1 Q^*_0 > 0$. This condition holds for sufficiently large values of $\tilde{\alpha}_0$, including all $\tilde{\alpha}_0 \geq \alpha_0$.

[10]The efficient amount of the public good is also allocated when the two communities have incorrect beliefs, as long as those beliefs are the same.

2: $-d(Q^*_{01} + Q^*_{A1})$. We highlight two results (see the Appendix for further results and derivations).

Result 1: If $d\alpha_{01} \leq 0$, then there exists $d\tilde{\alpha}_{01} > 0$ such that $d(Q^*_{01} + Q^*_{A1}) > 0$.

The first result says that even if the actual benefit to community 1 declines or stays the same, the total allocation of the public good to community 1 can increase if there is a sufficient increase in perceived value to the community. In this case, the efficient allocation to community 1, Q^*_{01}, is lower but the residents increase their lobbying by more than enough to offset this decline. This allocation is clearly inefficient since the total allocation to community 1 should decrease when the actual benefits from the public good decline.

Result 2: If $d\tilde{\alpha}_{01} > 0$ and $d\alpha_{01} > 0$, then $d(Q^*_{01} + Q^*_{A1}) > 0$.

The second result says that the total allocation to community 1 can also increase when there is a rise in the actual and perceived values of the public good. For example, if there is new information about the benefits of the public good and the agency and the community residents update the values of $\tilde{\alpha}_{01}$ and α_{01}, the total allocation to community 1 will increase.

Results 1 and 2 provide alternative reasons a community might receive more of a public good. In the empirical application, we distinguish between these competing explanations for observed increases in public good provision.

3 Behavioral biases in response to salient events

Within communities that have experienced a salient focusing event, heuristics can bias perceptions about the benefits of a public good and lead to changes in lobbying. Heuristics are mental "short-cuts," which provide fast and effortless judgments but can result in systematic biases (Kahneman, 2011). Under a variety of the common heuristics identified in scholarly work, salient events can lead to biases. As noted above, we describe events as salient in accordance with its plain language meaning of "standing out conspicuously; prominent" (Salient [Def. 1], 2018). For the application to public goods considered in this paper, the use of heuristics after the occurrence of salient events can lead to biased beliefs about the benefit of the public good. In terms of the theoretical model in the previous section, if the event leads to an upward bias in α_{01}, it can result in an increase in lobbying by the community and an inefficient provision of the public good (Result 1). In the remainder of this section, we describe three heuristics—availability, affect, and representativeness—under which salient events can lead to biased perceptions about the value of a public good.

Under the availability heuristic, people base judgments on information that is easiest to bring to mind or most "available." Information may be more available because it is less costly to obtain (e.g., Finkelstein, 2009; Chetty *et al.*, 2009; Sexton, 2015), it is distinct and tends to stand out (Bordalo *et al.*, 2012, 2013), it is more familiar (Lichtenstein *et al.*, 1978), or it is related to recent experiences (Tversky and Kahneman, 1974). When a salient event occurs, it can bias perceptions of the public good's value upwards by drawing the community's attention to the benefits that would come from mitigating the consequences of the salient event. As a result, communities affected by the event may increase lobbying for the public good and receive more of it. This same prediction could come about if people use the affect heuristic (Loewenstein *et al.*, 2001; Loewenstein and Lerner, 2003), in which their assessments are influenced by their emotional responses. If strong negative feelings are induced by a salient event, this could bias perceptions of benefits of a public good intended to mitigate the consequences of future such events upward and lead to increased lobbying and increased public goods provision.

Similarly, the representativeness heuristic can lead to overestimates of the public good's value if it causes individuals to misunderstand the stochastic process underlying the relevant hazard. Under the representativeness heuristic, people make judgments about probability based on how similar a sample is to some distribution. When individuals observe a sample containing a rare event or an unlikely sequence of events, the representativeness heuristic can lead them to change their beliefs about the underlying distribution, even when the sample is small (Tversky and Kahneman, 1974). The observation of an event, therefore, can cause individuals' beliefs to change and lead them to believe another event is forthcoming (e.g. Guryan and Kearney, 2008).[11] In our application, the observable implications of such a bias are identical to those caused by the availability or affect heuristics—communities that have experienced a salient event may have upwardly biased perceptions regarding the expected value of the public good, in this case because they overestimate the likelihood of another such event. If so, they may lobby government and be allocated more resources. Within our empirical application, this is possible even when objective benefits of the public good have declined. Since each of these behavioral biases results in the same observable implications, our empirical application does not distinguish between them.

4 Empirical application

4.1 Managing wildfire in the western U.S.

Federal agencies manage 250 million hectares of wildlands in the U.S., and 88% of public lands in the contiguous U.S. are in the western U.S. In recent decades, the threat of wildfire has increased in this region (Dennison *et al.*, 2014; Westerling, 2016) owing to factors including climate change (Moritz *et al.*, 2012; Westerling *et al.*, 2006; Yue *et al.*, 2013), the expansion of wildland-adjacent communities (Radeloff *et al.*, 2018), and historical fire exclusion (Arno *et al.*, 1995; Keane *et al.*, 2002; Naficy *et al.*, 2010). For much of the twentieth century, the USFS and other public agencies took aggressive steps to exclude fire from western forests through fire suppression. This led to a build-up of "ladder fuels," which carry fire from a forest's understory to its canopy and

[11] In principle, the representativeness heuristic can also lead to the opposite bias: if individuals observe an event but their belief in the underlying distribution persists, they may begin to believe the event is unlikely to recur, since this will cause the observed sequence to better resemble the known distribution.

can contribute to larger and more severe wildfires in some dry western forests. Due to increases in wildfire hazard, federal spending on wildfire management has risen in recent decades. Federal agencies spend approximately \$3 billion annually controlling wildfire (Gorte, 2013), and approximately one-half of the USFS budget is now dedicated to fire management (Thompson *et al.*, 2015).

Of this wildfire spending, roughly \$0.5 billion is allocated to fuels management projects, which involve removing fuels from the landscape through mechanical thinning and controlled burns (Agee and Skinner, 2005). The goal of these projects is to reduce the severity of wildfires (Stephens *et al.*, 2009) by restoring the forest to conditions under which high intensity fires are less likely. Removing understory vegetation can reduce the likelihood that trees will burn in high-severity canopy fires (Agee and Skinner, 2005). Fuels reduction projects within dry forests of the western U.S. are effective in reducing fire intensity, especially when prescribed fire and thinning are used together (Kalies and Kent, 2016). There is also evidence that strategically-placed fuels projects (Schoennagel *et al.*, 2017) can help prevent damage to homes and structures by reducing fire severity (Kennedy and Johnson, 2014) and allowing firefighters to defend homes (Bostwick *et al.*, 2011).

Communities that have recently experienced a close wildfire are likely to face lower risks of property damage from subsequent wildfires in the short term because fire is a contagion process whose spread depends on fuel availability. Fuels management projects and wildfires can both serve as barriers to the spread of subsequent fires and reduce their severity (Collins *et al.*, 2009; Parks *et al.*, 2015). Despite this reduced risk, these same communities may be subject to behavioral biases that lead them to overestimate the benefits of fuels management projects. Previous research indicates that communities are more attentive to wildfire risk following nearby wildfire incidents (McCoy and Walsh, 2018; Mockrin *et al.*, 2018). Therefore, there is potential in our application that community lobbying will increase after a nearby fire despite decreases in objective wildfire risk (see Result 1). We use data from across the western U.S. to evaluate whether communities that have experienced a recent, close wildfire are subsequently allocated more fuels management projects, even as this may be suboptimal given the reduced risk.

4.2 Data

To test the effects of responses to salient events on the provision of local public goods, we combine an extensive panel data set of the locations of fuels management projects on public lands with spatial data on wildfire perimeters and locations of wildland-adjacent communities. Due to the importance of wildfire management in the western U.S., we focus our attention on lands in 15 western states[12] managed by the U.S. Forest Service (USFS), Bureau of Land Management (BLM), and National Park Service (NPS). We identified these public lands using BLM and NPS boundaries (Bureau of Land Management, 2014) and administrative National Forest boundaries for USFS lands. Combined, our study area encompasses approximately 1.5 million square kilometers of federal land, of which the USFS and BLM manage roughly equal shares (47%), with the remaining 6% managed by the NPS. We divided this area into a grid of 1 km $\times$ 1 km cells, since this is the approximate size of the average fuels management project in our data. These 1 square kilometer cells are the units of analysis.

The fuels management data come from the National Fire Plan Operations and Reporting System (NFPORS). The NFPORS database records the point location (latitude and longitude), dates, and area of all fuels reduction projects for the USFS and the Department of Interior (including BLM and NPS) lands in the years 2003-2011. Projects are classified as controlled burns, mechanical thinning, preparation for treatment, and other. Controlled burns and mechanical thinning account for 94% of the observed projects in our data. Because NFPORS does not provide the boundaries of fuels management projects, we used the reported point location and area to estimate boundaries.

[12] These states are Arizona, California, Colorado, Idaho, Kansas, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oregon, South Dakota, Utah, Washington, and Wyoming.

Using ArcGIS, we created a polygon layer in which fuels management projects were represented by circles of the reported area, centered on the reported point location. A grid cell was designated as having received fuels reduction in a given year if the grid cell's centroid was inside of an imputed project boundary in that year.

Although the majority of land under federal management is forested (52%), there are significant areas in shrubs (39%) and grasslands (7%).[13] Our data reveal that fuels reduction projects are implemented on non-forest lands, but at a much lower rate than on forest lands. As shown in the first panel, second column of Table 1, for the whole sample the rate of fuels reduction projects in evergreen or mixed forests is 2.5%. The rate is lower (1.1%) in deciduous forests, which are more likely to occur in relatively wet areas where wildfire is less prevalent. In deciduous forests, prescribed fire is typically used to restore native tree species rather than for hazard reduction (Matlack, 2013; Brose *et al.*, 2001). Fuels management is uncommon on non-forest lands such as shrubs and grasslands (the rate is about 0.5% for the whole sample) because they have much lower volumes of flammable vegetation and, therefore, are a lower risk to neighboring communities. Since fuels reduction activities are concentrated in evergreen and mixed forests and the relationships between fire events, fuels reduction activities, and future fire risk are much less clear in deciduous forests and other land cover types (Keeley *et al.*, 2009; Moritz *et al.*, 2014), we focus our attention hereafter on forest (evergreen and mixed forests) lands.[14] For the forest-only sample, the USFS is the dominant land management agency (83% of all grid cells), followed by the BLM (13%) and the NPS (4%).

We define wildland-adjacent communities as wildland urban interface (WUI) Census blocks,

[13]We obtained these estimates by overlaying the National Land Cover Data for 2006 on the federal agency data described above.

[14]In results not reported here, we find evidence of government responsiveness to behavioral biases for deciduous forests and non-forest lands, although the estimated effects are much smaller and significant only in the year of the fire. Further, the main results presented below are qualitatively similar when we include deciduous forests and non-forested lands in the sample.

which encompass both interface, where developed residential areas directly abut large areas of wildland vegetation, and intermix, where residences are dispersed among wildland vegetation (USDA and DOI, 2001). Wildland urban interface data come from Radeloff *et al.* (2005), who mapped U.S. WUI areas using landcover and housing density data. For our purposes, we consider as WUI any U.S. Census block within our study region that Radeloff *et al.* (2005) classified as low, medium, or high density interface or intermix in 2000. Descriptive statistics for all WUI blocks in the study region are provided in the second column of Table 2.

Fire data come from the interdepartmental Monitoring Trends in Burn Severity (MTBS) project (Eidenshink *et al.*, 2007). In the western U.S., MTBS uses Landsat satellite imagery to map fire perimeters for fires larger than 1000 acres (approximately 4 km^2). This focus on larger fires makes sense for this study, since we expect larger fires to be most salient to the public.

Our analysis relies on two distance measures: the distance from each forested grid cell to its nearest WUI blocks to associate forested areas that may be subject to management with communities and the distance from each WUI block to the nearest fire to identify salient fires. For each cell, we calculated the straight-line distance to up to 500 of the nearest WUI blocks within a threshold distance of 10 km. Among the nearly 1.5 million grid cells in our sample, only 3,147 were matched with the maximum number of WUI blocks. Therefore, limiting the sample to the closest 500 WUI blocks is unlikely to influence our results. In a similar way, we measured the straight-line distance from each WUI block to the nearest fire in each year. Figure 1 provides the kernel density functions for the two distance measures. For forested cells, distances of less than 13 km to the nearest WUI block are the most common. The density for distances between WUI blocks and the nearest fire is roughly uniform, although the likelihood of fires within 15 km or more than 40 km away is somewhat lower.

Our empirical strategy requires dropping grid cells that are not close to at least one WUI block, since we expect the placement of fuels reduction activities far from human settlement to be determined by factors other than the behavioral biases due to salient wildfires (e.g., protection of timber resources). In our main set of results, the sample consists only of grid cells closer than 5 km from the nearest WUI block. As described below, however, we test the sensitivity of our results to different definitions of closeness to WUI blocks. Compared to the whole sample of grid cells, the rate of fuels reduction projects increases somewhat when we consider only grid cells within 5 km of a WUI block, but the rate is still highest on forest lands (Table 1, panel II). Restricting our attention to grid cells within 5 km of a WUI reduces the number of WUI blocks by 77%, but has little effect on average community characteristics (Table 2).

To test whether learning can explain our results, we use a measure of vegetation condition from the Landfire project.[15] The Vegetation Condition Class (VCC) is a cardinal measure of the degree to which the current vegetation departs from simulated historical vegetation conditions. For example, the largest value of VCC corresponds to "high departure", which is indicative of a landscape on which fuels have built up due to long-term fire suppression. A fine-scale measure of the VCC is available for 2001, 2008, and 2012, which we match to the grid cell data described above. Further tests are conducted with measures of population and number of housing units (Table 2). Because access to block-level U.S. Census data is restricted, these variables are measured at the Census tract level using data from the 2000 Census.

[15] Landfire is a partnership of U.S. land management agencies to provide geospatial data on vegetation, wildland fuel, and fire regimes. See `https://www.landfire.gov/about.php#planning` (accessed August 31, 2017).

5 Econometric model & results

5.1 Overview

The essence of our empirical approach is to determine whether fuels management projects are more likely to occur on federal lands that are close to WUI communities that have experienced nearby wildfires. We expect WUI residents to be more affected by biases if they can observe smoke plumes, fire-fighting efforts, and possibly the fire itself. Such highly localized effects of wildfires are supported by findings in McCoy and Walsh (2018) that fires influence housing prices only if they are within 5 km.

We motivate our empirical approach with Figure 2, which shows a small portion of our study area in the state of Oregon. Light shaded areas depict lands managed by federal agencies, and dark shaded areas are Census blocks classified as WUI. The hatched area is the burn scar from a fire that occurred in 2011. We think of WUI communities as being "treated" by close fires in the sense that the salient fire can raise the expected value of fuels treatments for residents of the community. Our definition of close is varied in the empirical analysis, but for this illustration it is defined as 5 km. As such, WUI community A is treated because it is within 5 km of the fire, but WUI communities farther than 5 km from the fire are untreated. We then consider whether there is a higher probability of fuels reduction projects occurring in close proximity to the treated WUI community. We identify all grid cells on federal lands that are within 5 km of some portion of a WUI community. Grid cells 1 and 2 meet this criterion (the radius of the solid circle is 5 km). However, only grid cell 1 is close (within 5 km) to at least one treated WUI community (A), whereas grid cell 2 is close to untreated communities. We test whether grid cells that are close to WUI communities that are close to fires (e.g., cell 1) are more likely to receive a fuels management project than grid cells that are close to WUI communities that have not experienced a nearby fire (e.g., cell 2).

As illustrated in Figure 2, cells near treated WUI communities are themselves not necessarily close to or within areas that recently burned. This is by design, since we hypothesize that behavioral biases will increase demand for fuels reduction projects throughout the area surrounding a community that has experienced a recent wildfire event. An implication is that fuels projects motivated by the occurrence of salient wildfires may be relatively distant from the sites of recent wildfires. Because they decrease the volume of flammable fuels, fires reduce the marginal benefits from subsequent fuels management projects located nearby or, at a sufficient distance from the fire, leave benefits unchanged. Therefore, while we do not measure explicitly the efficiency consequences of bias-driven management, the principles of fire science imply that such management can only (weakly) diminish the benefits of fuels projects.

In place of distance to an event, some recent studies have used more direct measures of information transmission as indicators of salient events. Gallagher (2014) uses the number of local television stories on floods as a measure of media exposure that indicates salience. For our application, however, media markets are large relative to the scale at which we expect the effects of wildfires to operate. In the western U.S., local television media markets are comprised of many counties and, in some cases, large portions of states.[16] Furthermore, to identify effects of media coverage we would need to omit from our model year-by-region fixed effects that are defined at much smaller scales than media markets. A second possible way to operationalize whether a fire is salient is by whether the fire is visible, since McCoy and Walsh (2014) find that a wildfire has a larger effect on housing prices if the burn scar is visible from a house. Measuring the visible features of a wildfire is difficult in our case because we are interested in effects on communities of people rather than single points in space. Communities are delineated with Census blocks, which are often large

[16]See `http://www.nielsen.com/intl-campaigns/us/dma-maps.html` (accessed August 31, 2017).

in the low density WUI areas we study. Because of the limitations of media markets or visibility in this context, we use distance as an indicator of whether a fire is salient. We present tests, below, that strengthen our case for using distance to indicate the degree to which communities are likely to be subject to behavioral biases due to the occurrence of a salient wildfire.

5.2 Main specification

As in recent applications of the difference-in-differences estimator (e.g. Conley and Taber, 2011; Abrevaya and Hamermesh, 2012), we estimate our main specification using a linear probability model. In a panel data setting, the advantage of the linear probability model is the ease of including fixed effects. In our application, fixed effects play a critical role in controlling for unobserved determinants of fuels reduction activities, such as underlying fire hazard and proximity to assets at risk. An alternative is a binary probit or logit specification. However, including fixed effects in these models gives rise to the incidental parameters problem that renders maximum likelihood estimates inconsistent. The linear probability model is a good alternative considering that all of our regressors are dummy variables and our goal is to estimate their effects at the mean of the data (Wooldridge 2010).

The main specification of the linear probability model is:

$$y_{it} = \sum_{\ell=-4}^{0} \beta^{\ell} \mathbb{1}\{\exists s \in S_i : firedist_{s,t+\ell} \leq c\} + \gamma_i + \delta_{tm(i)} + \epsilon_{it} \tag{8}$$

where i, t, and s, index cells, years, and WUI blocks, respectively, and $m(i)$ is a mapping from cell i to an aggregate geographical region (e.g., a Census tract), indexed by m. The dependent variable, y_{it}, equals 1 if a fuels management project occurs on cell i in year t and is 0 otherwise. $S_i = \{s : wuidist_s \leq d\}$ where $wuidist_s$ is the distance from cell i to WUI block s and d is a threshold value. Thus, S_i is the set of all WUI blocks within distance d of cell i. The salient wildfire indicator function $\mathbb{1}\{\cdot\}$ equals one when a fire occurs close to at least one of the WUI blocks in the set S_i. Specifically, $firedist_{s,t+\ell}$ is defined as the distance to the fire closest to WUI block s that occurs in year $t+\ell$. If that fire is within distance c of WUI block s and block s is in the set S_i, then the indicator function equals one. The parameters of the model are γ_i, β^ℓ, and $\delta_{tm(i)}$, and ϵ_{it} is a random disturbance term. The summation term in equation (8) allows each fire to have a contemporaneous effect on the probability of fuels management projects ($\ell = 0$) and four annual lagged effects ($\ell =$ -1 to -4). We examined specifications with more lags, but did not find any significant coefficients outside the range of effects in equation (8).

We identify the effects of salient wildfires based on within grid cell and within year-by-region variation. We would expect decisions about fuels management projects to be influenced by such factors as fire hazard, access, and administrative unit. We implicitly control for these time-invariant factors with cell-level fixed effects γ_i.[17] Time-varying factors could include macroeconomic trends affecting government budgets, fluctuations in weather, and changes in management objectives. We control for these factors with year-by-region effects $\delta_{tm(i)}$ where regions are alternatively defined as units (USFS national forests, BLM district offices, NPS national parks), districts (USFS ranger districts, BLM field offices), counties, and Census tracts. Districts are less aggregated than units[18] and Census tracts are less aggregated than counties. But these regions are sufficiently small areas so that within-region variation in fire risk trends should be minimal, helping to rule out learning as an alternative to behavioral biases.[19] We also consider the degenerate case of a single region, which amounts to including year effects.

We are concerned about the possibility of spatial autocorrelation, which can bias estimates

[17]With fixed effects included, cells that are never included in fuels management projects have no influence on the model estimates.

[18]For NPS lands, there is no region less aggregated than a unit (National Park); therefore, year-by-district fixed effects and year-by-unit fixed effects are equivalent on NPS lands.

[19]We discuss potential time-varying determinants of fire risk in more detail, below, when we evaluate learning as an alternative explanation for our results.

of standard errors. If, for example, fuels reductions span more than one grid cell, then the fuels reduction status of neighboring grid cells may be correlated. To account for this possibility, we cluster the residuals in two ways, first at the district level and next at the unit level. As a check of robustness, we also estimated our main specifications with clustering at the level of Census tracts and counties. Our choice of geographic unit on which to cluster does not substantively affect our results.

The results for the main specification are reported in Table 3. All model versions include cell fixed effects (γ_i) and consider pixels and wildfires within 5 km of WUI blocks (i.e., $c = d = 5km$). The models vary according to the type of year-by-region fixed effects included. Model (1) includes only year effects. We find the contemporaneous effect of a close wildfire on the probability of a fuels reduction project to be 1.6 percentage points, an estimate that is significantly different from zero at the 1% confidence level. We interpret the contemporaneous effect as an immediate response to a wildfire.[20] The effect is large relative to the 3.5% average annual rate of fuels reduction projects in the evergreen and mixed forests in our sample (panel II in Table 1). We also find a significant effect ($p < 0.05$) of a close fire that occurred one year previously, but only when we cluster the errors at the district level. This effect is smaller, indicating that a fire last year raises the probability of a fuels reduction project by 0.7 percentage points. Fires that occur two, three, and four years earlier do not have significant effects.

The inclusion of year-by-region effects sharpens the results. In models (2) through (5), the contemporaneous effect remains at approximately 1.6-1.8 percentage points, but now the one-year lagged effect is significantly different from zero, whether clustering of standard errors is at the unit or district level. The results indicate that a close fire one year ago increases the probability of fuels management by 0.6 to 0.9 percentage points. In models (3), (4), and (5), longer lags do not

[20]Alternatively, fuels reduction projects could be accurately placed in anticipation of wildfires. We examine this possibility, below, with a specification that includes lead effects of wildfires, and find little evidence for it.

have significant effects; however, the two-year lag in model (2) is significantly different from zero at the 5% level when standard errors are clustered at the district level. The estimate of 0.6 is lower than the one-year lagged effect (0.8), adding further evidence that the behavioral biases due to the salient fire diminish with the time since the fire.

5.3 Sensitivity analysis and robustness checks

We conduct sensitivity analyses and robustness checks on our main specification. The first test evaluates the sensitivity of our results to the definition of close fires (fires within a distance c of the WUI) and close cells (cells within a distance d of the WUI). Figure 3 presents the coefficients on the $firedist$ variable for all combinations of $c = 2, 5, 10$ and $d = 2, 5, 10$, using version (2) of the model in Table 3. The lines in each panel correspond to different definitions of close fires and the three panels correspond to different definitions of close grid cells. For example, when we limit close fires and close cells to those within 2 km ($c = d = 2$; the dashed line in Panel A), we find that a close fire raises the probability of a fuels management project by approximately 2.5 percentage points. The effect is strong and persistent to a three-year lag (coefficient values marked by a solid triangle are significantly different from zero at the 5% level and those marked by an “x” are not).

Taken together, the results in Figure 3 provide support for the use of distance to indicate the presence of salient wildfires, with their prospect of triggering behavioral biases. First, fires that occur closer to WUI residents have larger effects. In all three panels, the dashed line, corresponding to fires within 2 km, is always above the dashed-dotted line, corresponding to fires within 10 km. Expanding the fire proximity threshold (c) is likely to include fires that are not as salient to WUI residents, making them less likely to trigger heuristics in decision-making. Second, for a given fire, effects of a salient wildfire are amplified at distances close to WUI residents. Lines in Panel A, corresponding to grid cells within 2 km of WUI blocks, tend to be higher than those in panel C, corresponding to grid cells within 10 km of WUI blocks. When we expand the size of the window around WUI blocks (d), we include fuels management projects that provide few benefits to satisfy the demands of WUI residents concerned with wildfire risk. Third, the effect of a close wildfire falls off over time, consistent with residents subject to recency bias.

The second set of sensitivity analyses considers the possibility of serial correlation in our data. There may be negative serial correlation if management agencies are less likely to undertake a fuels management project in locations where fuels have recently been reduced. On the other hand, there may be positive serial correlation if projects take more than one year to complete or if fuels management projects take place in adjacent areas over several years and we mismeasure the precise boundaries of these activities.[21] Statistics in Table 1 show that, conditional on a fuels reduction project taking place, most grid cells receive fuels management only once. However, it is not uncommon for grid cells to receive fuels management two or more times. We address serial correlation by recoding the dependent variable so that a multi-year fuels management project appears as a single-year project (Table 4). For example, if $y_{it} = y_{it+1} = 1$, we recode the variables as $y_{it} = 1$, $y_{it+1} = 0$. In general, when we observe a cell with consecutive values of one, we set all but the first value to zero. This recoding procedure has the effect of purging the data of serial correlation due specifically to multi-year fuels reductions. We estimate all versions of the main specification with the recoded data and find little difference in the results.[22]

We estimate a version of equation (8) with one- and two-year leads (Table 5) as a placebo test, as we would not expect the likelihood of observing a fuels reduction project today to be influenced

[21] This is possible given the way we define boundaries for fuels reduction projects, described in section 4.2.

[22] Another way to test whether our results are robust to the possibility of serial correlation is with the estimator in Arellano and Bond (1991). We estimate versions of equation (8) that include one- and two-year lagged dependent variables. The results, available from the authors upon request, provide evidence of positive serial correlation. The coefficients on the lagged dependent variables are positive and significantly different from zero. Nevertheless, we still find evidence of contemporaneous effects of close fires on the likelihood of fuels management projects. The effects of fires in previous years are no longer significant, most likely because the lagged dependent variables absorb the effects of past fires.

by the occurrence of future fires. Significant lead effects could be due to omitted time-varying cell-level factors that are correlated with wildfires and fuels reduction projects. Formally, lead parameters are included by modifying the summation term in equation (8) so that ℓ takes values from -4 to 2. A finding of insignificant lead coefficients gives us further confidence that we identify causal effects of wildfires on government agency decisions and are not simply finding that agencies locate fuels management projects in areas that are likely to experience wildfires. The estimated coefficients on the lead variables are small relative to the contemporaneous and lagged parameters and not significantly different from zero with the exception of the two-year lead in models (2) and (5). Estimates of the other model coefficients are largely unaffected.

Although our data only includes pre-fire fuels reduction projects (predominantly controlled burns and mechanical thinning), it is conceivable that some post-fire activities could be misclassified as fuels management. Soon after a fire, land managers may thin trees, clear debris, and conduct salvage logging in the area where a fire occurred. In this case, we might misinterpret post-fire clean-up activities as a response by managers to the salient event. We guard against this possibility by dropping all observations within the perimeter of an earlier fire (Table 6).[23] This is likely an overly conservative approach as we may discard information about fuels reduction activities that occurred in response to a later fire occurring within the perimeter of an earlier fire. Nevertheless, we continue to find a significant contemporaneous effect and, in model (2), a one-year lagged effect that is significant at the 5% level.

5.4 Learning as an alternative to behavioral biases

An alternative interpretation of our empirical results is that government agencies and the public learn about risks from future fires when a wildfire occurs. In the theory, this corresponds to

[23] Wildfires never burn all of the vegetation within the fire perimeter. Therefore, clean-up activities are most likely to occur inside the perimeter.

the case in which a fire event causes the agency and the community to update and increase, respectively, the values of α_{01} and $\tilde{\alpha}_{01}$ (Result 2). The key question to ask is, what information could a wildfire provide to managers and the community to allow them to learn about the likelihood of a future fire? The three categories of determinants of large wildfires in the western U.S. over the period 1984-2008 that managers and communities could learn about are ignitions, climate, and topography/vegetation (Parisien *et al.*, 2012). The elements of some of these factors are not applicable to our study of public forest lands (population density and land use) and others are controlled for by the grid-cell level fixed effects (topographic roughness and road density[24]) and year-by-region fixed effects in our model (large-scale measures of lightning strikes). Parisien *et al.* (2012) find that wildfire probability is predicted by a number of climate variables, including long-term temperature, precipitation, and wind speed means. It is conceivable that weather distributions changed over the period of analysis (i.e., climate change occurred) or that there were sustained periods of weather anomalies such as droughts or extended rainy periods. Wildfires may have alerted land managers and communities to the effects of these events on future fire risk. However, because climate change and weather anomalies tend to be large-scale phenomena, they are also controlled for by the year-by-region fixed effects.[25] The smallest region used in our analysis is the Census tract, which has an average size of 364 km^2. For comparison, the land area of Martha's Vineyard in Massachusetts is 227 km^2 and Lake Tahoe in California is 495 km^2 in size; weather anomalies are likely to be constant within such small areas.

The remaining determinant of wildfire that could vary within the scale of the region-by-year fixed effects is the condition of the local vegetation. Although we expect the fixed effects in our model to control for most of the key determinants of fire risk about which agencies and communities could

[24]Parisien *et al.* (2012) indicate that there was little year-to-year variation in topographic roughness and road densities over the period 1984-2008, which mostly covers our study period.

[25]Parisien *et al.* (2012) find that the capacity of a site to produce biomass, measured as gross primary productivity, is also associated with wildfires, but indicate that productivity is largely determined by climate.

learn, we provide a formal analysis using the Vegetation Condition Class (VCC) measure described above. The VCC indicates the amount of fuels on the landscape and, thus, the potential for severe wildfires. If managers learn about vegetation conditions from local wildfires and the fixed effects in our model do not adequately control for fire hazard, then the response to a nearby wildfire should be magnified when there are heavy fuel loads. We investigate this hypothesis by interacting the VCC variable with the treatment variable:

$$
\begin{aligned}
y_{it} = &\sum_{\ell=-4}^{0} \beta^{\ell} \mathbb{1}\{\exists s \in S_i : firedist_{s,t+\ell} \leq c\} \\
&+ \zeta \sum_{\ell=-4}^{0} [VCC_{i,t+\ell} \times \mathbb{1}\{\exists s \in S_i : firedist_{s,t+\ell} \leq c\}] + \gamma_i + \delta_{tm(i)} + \epsilon_{it}
\end{aligned}
\tag{9}
$$

where $VCC_{i,t+\ell}$ is the condition class for cell i in year $t+\ell$ and ζ is a model parameter. If the estimate of ζ is positive and significantly different from zero, then the effect of a wildfire on the probability of a fuels management project increases with fuels loads. However, results in Table 7 reveal an insignificant effect of VCC, in opposition to the learning model in Result 2.[26] The original estimates of the β coefficients are unchanged when we include the VCC interaction term.

5.5 Additional support for the role of behavioral biases

To provide additional support for behavioral biases as the source of observed changes in fuels management projects, we show that the effects of close fires vary with characteristics of WUI communities and the size of fires. We estimate two sets of models with interactions similar to (9).[27]

[26] In equation (9), ζ is restricted to be the same for the contemporaneous and lagged effects. We use this parsimonious specification because we do not have strong *a priori* reasons to expect the marginal effects of VCC to differ by the length of the lag. We estimated alternative models that allow each lag to have a different coefficient. Based on F-tests reported in Table 7, we cannot reject the null hypothesis that the coefficients are equal.

[27] As in equation (9), ζ is restricted to be the same for the contemporaneous and lagged effects. According to F-tests reported in Table 7, we cannot reject the null hypothesis that the coefficients are equal.

The first version is specified:

$$y_{it} = \sum_{\ell=-4}^{0} \beta^{\ell} \mathbb{1}\{\exists s \in S_i : firedist_{s,t+\ell} \leq c\}$$
$$+ \zeta \sum_{\ell=-4}^{0} \sum_{s \in S_i} [z_s \times \mathbb{1}\{firedist_{s,t+\ell} \leq c\}] + \gamma_i + \delta_{tm(i)} + \epsilon_{it} \tag{10}$$

where z_s is a characteristic of WUI block s or of the fire that treats block s. We define z_s as, alternatively, the population of the Census tract, the number of housing units in the Census tract, and logged fire size.[28] The second version of the model in (10) includes VCC as a control for objective fire risk.

Results in Table 7 reveal that the effects of a close wildfire are larger as the population and the number of housing units increase. The finding that effects of close fires vary with community characteristics shows that local residents are part of the allocation mechanism (see also Anderson *et al.*, 2013). The coefficient for fire size is positive but significantly different from zero at only the 8% level. The lack of significance may be due to the fact that the fire data we use only includes relatively large fires. Finally, we find that the effects of resident characteristics and fire size are unchanged when we control for landscape conditions with the VCC variable. This suggests that fuels management decisions depend on perceived benefits subject to behavioral biases rather than on learning about objective benefits.

6 Conclusions

The economics literature on behavioral biases has focused on how consumption of private goods is affected by features of the choice problem. In this paper, we extend this literature to examine how

[28] We estimate the fire size version of the model with the sample used to produce Table 6. A salient wildfire could result in behavioral biases but also limit the area available for fuels treatments. By using the restricted sample, our estimate measures only the first effect.

behavioral biases can affect the government provision of public goods. In our theoretical model, the government decides how much of a local public good to allocate, taking into account the lobbying activity of the public. Due to common decision-making heuristics, a salient event such as a wildfire can increase the perceived benefit of the good among the public. The public then lobbies for more of the public good, leading the government, which pays a cost for ignoring its constituents, to allocate more than the efficient amount of the public good. This can occur even when the salient event has lowered the true benefit of the good.

The empirical results support our theory that behavioral biases can influence public goods provision. We find that federal land management agencies in the western U.S. are more likely to locate fuels management projects near communities that have experienced a recent nearby wildfire. This increased response comes even as the recent wildfire has likely decreased the likelihood of loss from future fires and, therefore, the current value of fuels management projects. With our main specification, we estimate that the probability of a fuels management project increases by 1.6 to 1.8 percentage points in the year the fire occurs and by 0.6 to 0.9 percentage points in the year after the fire. These are relatively large changes considering that the average annual rate of fuels management projects on all forested lands in our sample is approximately 3.5%. Our finding that the effects of the nearby wildfire attenuate after one or two years is consistent with attenuation of behavioral biases among the public over a short time horizon, as found by McCoy and Walsh (2018), and with recency bias. However, our results are also consistent with a prompt response by the government that satisfies the increased demand for fuels management. One way to investigate the dynamics of government and community responses to salient wildfires would be to consider WUI blocks that experience nearby fires in multiple years and see how the effects change over time. For this analysis we would need a data set covering a longer time period.

The results of robustness checks indicate that the salience of wildfires drives the behavioral biases. First, we find that the effects of nearby wildfires on the likelihood of observing fuels management projects are strengthened when we focus our analysis on closer fires, which should be more salient to WUI residents (Figure 3), making them more likley to lead to behavioral biases. The effects also increase when we consider grid cells closer to WUI communities, suggesting that the federal agencies are responding to heightened demand for fuels management projects. Second, we find that effects of nearby wildfires increase with the population of the WUI community and the number of housing units (Table 8). These results suggest that the residents of WUI communities are part of the mechanism for determining the location of fuels management projects, consistent with a role for behavioral biases in decision-making. Finally, we find evidence that contradicts alternative explanations for our results. The finding of insignificant coefficients on lead variables suggests that agencies are not simply locating fuels management projects in places that are likely to have fires. The finding that vegetation condition does not magnify the effects of nearby fires guards against the possibility that our results reflect learning by agencies about the risk of future fires.

In addition to local public goods such as fuels management on public lands, behavioral biases could affect the government provision of national-level public goods in other contexts where salient events may act as a catalyst for government action (Anderson *et al.*, 2018). In response to the Exxon Valdez oil spill in 1989, the U.S. Congress passed the Oil Pollution Act of 1990 that required double hulls on oil tankers. The Three Mile Island nuclear accident in 1979 led to stricter controls on nuclear plants and the outbreak of West Nile virus in New York City in 1999 prompted the creation of a national surveillance system for infectious diseases in the U.S. Catastrophic flooding of the Mississippi River has often been followed by government-funded levee building and other channel engineering projects (Wright, 2000). The September 11, 2001 terrorist attacks in the U.S. were followed by military operations and government investment in security. These may be rational responses by the government to new information about the level of risk. However, our paper offers an alternative explanation. The public's demand may be distorted by the salience of the catalyzing event, which could mean that the government response to heightened demand for public goods is inefficient.

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7 Appendix

We evaluate the differential $d(Q^*_{01}+Q^*_{A1})$ defined in Equation (7). Using the definition $Q^*_{01} = \frac{\alpha_{01}}{\alpha_1+2\eta}$ and Equation (5), we obtain:

$$d(Q^*_{01}+Q^*_{A1}) = \frac{d\alpha_{01}}{\alpha_1+2\eta} + \frac{\gamma}{2(\gamma-\alpha_1)}\left(\left(\frac{\partial Q^*_{L1}}{\partial\tilde{\alpha}_{01}} - \frac{\partial Q^*_{L2}}{\partial\tilde{\alpha}_{01}}\right)d\tilde{\alpha}_{01} + \left(\frac{\partial Q^*_{L1}}{\partial\alpha_{01}} - \frac{\partial Q^*_{L2}}{\partial\alpha_{01}}\right)d\alpha_{01}\right) \tag{11}$$

To evaluate the partial derivatives in Equation (11), we rewrite the expressions for Q^*_{L1} and Q^*_{L2} in Equation (6), distinguishing the values of $\tilde{\alpha}_{01}$, $\tilde{\alpha}_{02}$, Q^*_{01}, and Q^*_{02}:

$$\begin{aligned} Q^*_{L1} &= K_0\left(\tilde{\alpha}_{01} - \alpha_1 Q^*_{01} + \frac{\alpha_1^2\gamma}{2(\gamma-\alpha_1)}(Q^*_{01}-Q^*_{02})\right) + K_1 Q^*_{L2} \\ Q^*_{L2} &= K_0\left(\tilde{\alpha}_{02} - \alpha_1 Q^*_{02} + \frac{\alpha_1^2\gamma}{2(\gamma-\alpha_1)}(Q^*_{02}-Q^*_{01})\right) + K_1 Q^*_{L2} \end{aligned} \tag{12}$$

where $Q^*_{02} = \frac{\alpha_{02}}{\alpha_1+2\eta}$. We obtain Equation (6) when $\tilde{\alpha}_0 = \tilde{\alpha}_{01} = \tilde{\alpha}_{02}$ and $\alpha_0 = \alpha_{01} = \alpha_{02}$. Substituting for Q^*_{L2} and Q^*_{L1} and collecting terms, we have:

$$\begin{aligned} Q^*_{L1} = \frac{1}{1-K_1^2}\Bigg[&K_0\left(\tilde{\alpha}_{01} - \alpha_1 Q^*_{01} + \frac{\alpha_1^2\gamma}{2(\gamma-\alpha_1)}(Q^*_{01}-Q^*_{02})\right) \\ &+ K_0K_1\left(\tilde{\alpha}_{02} - \alpha_1 Q^*_{02} + \frac{\alpha_1^2\gamma}{2(\gamma-\alpha_1)}(Q^*_{02}-Q^*_{01})\right)\Bigg] \\ Q^*_{L2} = \frac{1}{1-K_1^2}\Bigg[&K_0\left(\tilde{\alpha}_{02} - \alpha_1 Q^*_{02} + \frac{\alpha_1^2\gamma}{2(\gamma-\alpha_1)}(Q^*_{02}-Q^*_{01})\right) \\ &+ K_0K_1\left(\tilde{\alpha}_{01} - \alpha_1 Q^*_{01} + \frac{\alpha_1^2\gamma}{2(\gamma-\alpha_1)}(Q^*_{01}-Q^*_{02})\right)\Bigg] \end{aligned} \tag{13}$$

Taking partial derivatives of Q^*_{L1} and Q^*_{L2}, we obtain the expressions from Equation (11):

$$\begin{aligned} \left(\frac{\partial Q^*_{L1}}{\partial\tilde{\alpha}_{01}} - \frac{\partial Q^*_{L2}}{\partial\tilde{\alpha}_{01}}\right)d\tilde{\alpha}_{01} &= \frac{K_0}{1-K_1^2}(1-K_1)d\tilde{\alpha}_{01} \\ \left(\frac{\partial Q^*_{L1}}{\partial\alpha_{01}} - \frac{\partial Q^*_{L2}}{\partial\alpha_{01}}\right)d\alpha_{01} &= \frac{K_0}{1-K_1^2}(1-K_1)\left(\frac{\alpha_1^2\gamma}{\gamma-\alpha_1}\frac{1}{\alpha_1+2\eta}\right)d\alpha_{01} \end{aligned} \tag{14}$$

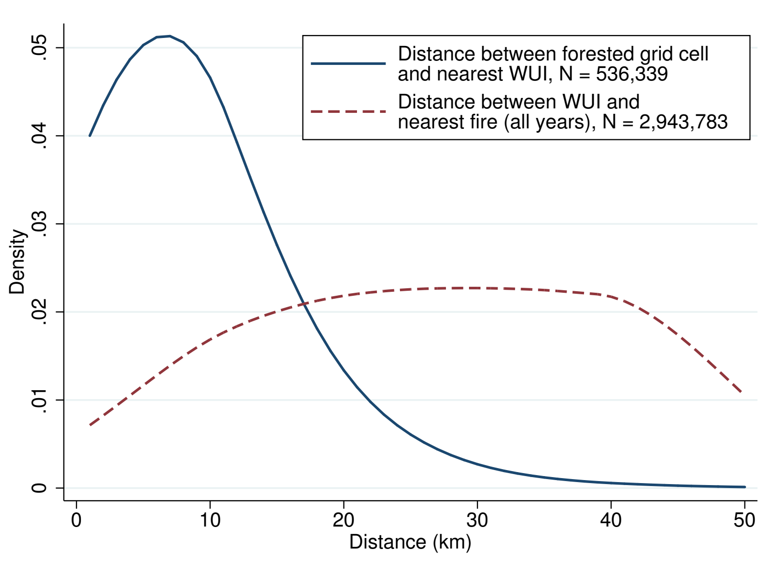
Because $K_1 < 1$ and $\gamma - \alpha_1 > 0$, the expressions in Equation (14) have the same signs, respectively, as $d\tilde{\alpha}_{01}$ and $d\alpha_{01}$.

We derive three results. Result 1: if $d\alpha_{01} \leq 0$, then there exists $d\tilde{\alpha}_{01} > 0$ such that $d(Q^*_{01} + Q^*_{A1}) > 0$; Result 2: if $d\tilde{\alpha}_{01} > 0$ and $d\alpha_{01} > 0$, then $d(Q^*_{01}+Q^*_{A1}) > 0$; and Result 3: if $d\tilde{\alpha}_{01} < 0$ and $d\alpha_{01} < 0$, then $d(Q^*_{01}+Q^*_{A1}) < 0$. Result 2 follows from the fact that when $d\tilde{\alpha}_{01} > 0$ and $d\alpha_{01} > 0$, all terms in Equation (11) are positive, and conversely for Result 3. For Result 1, each of the $d\alpha_{01}$ terms are weakly negative. Thus, we need for the $d\tilde{\alpha}_{01}$ term to be sufficiently large. Specifically, if:

$$d\tilde{\alpha}_{01} > -\left(\frac{\alpha_1^2\gamma}{\gamma-\alpha_1}\frac{1}{\alpha_1+2\eta} + \frac{1-K_1^2}{K_0(1-K_1)}\frac{1}{\alpha_1+2\eta}\right)d\alpha_{01} \tag{15}$$

then $d(Q^*_{01}+Q^*_{A1}) > 0$.

Figure 1: Kernel density plots of the distributions of distance to WUI and distance to nearest fire within the sample of forested grid cells and WUI blocks, respectively



Note: Kernel density functions are Epanechnikov with bandwidth 5. Distributions are across observations for which the target layer is closer than 50 km. There are 372 grid cells for which the nearest WUI block is further than 50 km. There are 4.8 million WUI block-years for which the nearest fire is further than 50 km.

Figure 2: Illustration of the data and empirical design

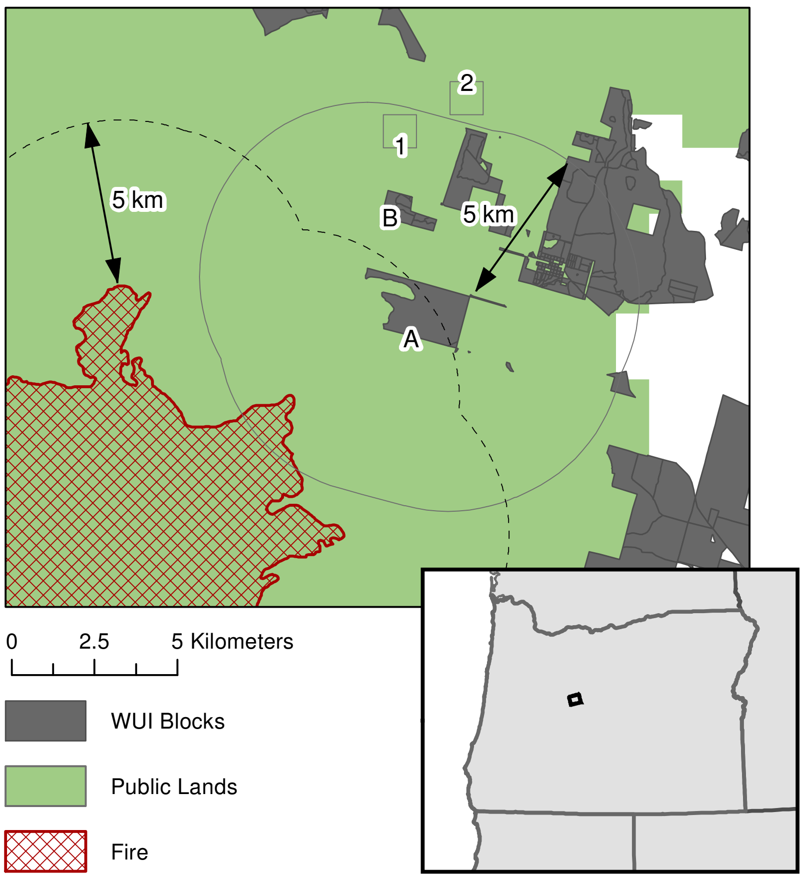
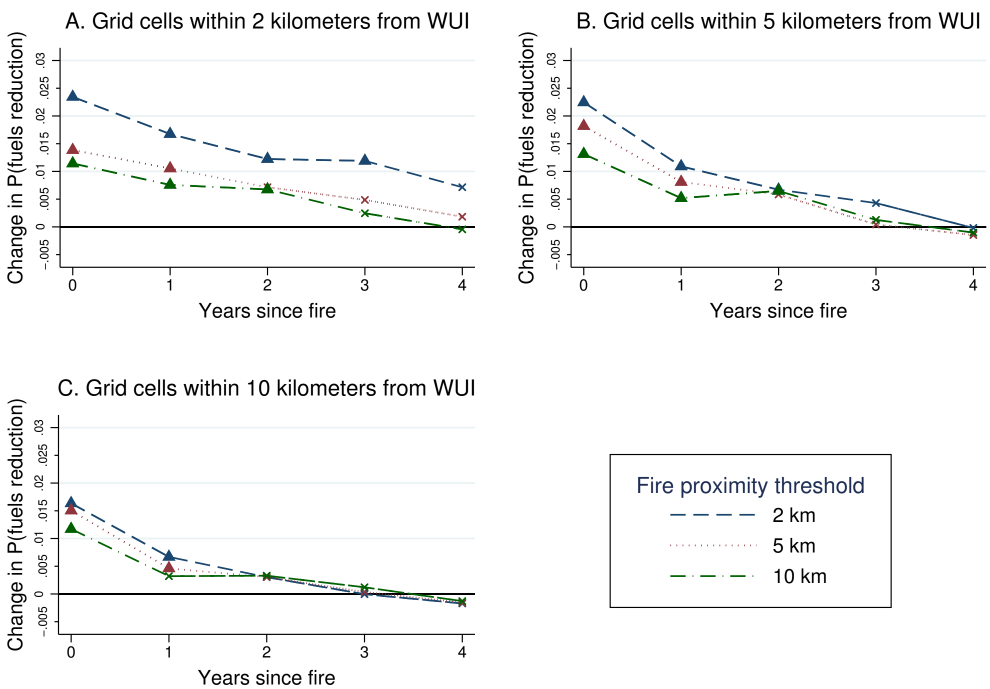


Figure 3: Sensitivity analysis for definitions of close fires and close public land grid cells



Note: Coefficients marked with a solid triangle are significantly different from zero at a 5% significance level when standard errors are clustered by unit. Coefficients marked with an x are not significantly different from zero.

Table 1: Rates of fuels management projects by land cover type

	Rate of fuels management		Fuels management projects per grid cell				
	Mean	No. obs. (grid cell-years)	None	Once	Twice	3 or more times	No. obs. (grid cells)
I. All grid cells							
Evergreen or mixed forest	0.025	4,830,399	0.86	0.089	0.030	0.020	536,711
Deciduous forest	0.011	211,077	0.93	0.052	0.013	0.005	23,453
Shrubland	0.005	6,392,430	0.97	0.022	0.006	0.003	710,270
Herbaceous	0.006	1,105,470	0.96	0.025	0.007	0.005	122,830
Other	0.005	472,635	0.98	0.015	0.005	0.004	52,515
Total	0.013	13,012,011	0.93	0.047	0.015	0.010	1,445,779
II. Grid cells $<$ 5 km from WUI							
Evergreen or mixed forest	0.035	1,864,575	0.82	0.108	0.041	0.033	207,175
Deciduous forest	0.012	98,073	0.92	0.057	0.014	0.006	10,897
Shrubland	0.010	1,450,062	0.95	0.035	0.011	0.008	161,118
Herbaceous	0.011	246,996	0.94	0.038	0.012	0.009	27,444
Other	0.012	103,482	0.94	0.037	0.013	0.011	11,498
Total	0.022	3,763,188	0.88	0.072	0.026	0.020	418,132

Note: Land categories taken from the 2006 National Land Cover Database (Fry *et al.*, 2011). Evergreen forests and deciduous forests consist of greater than 75% evergreen and deciduous trees, respectively. Mixed forests are areas where neither evergreen nor deciduous tree species dominate. Shrubland is areas dominated by shrubs less than 5 meters tall. Herbaceous land includes land dominated by grasses or other herbaceous vegetation. Other includes planted or cultivated land, developed land, wetlands, barren areas, and water. For example, on evergreen and mixed forests, 2.5% of our grid cell-year observations are treated (our dependent variable equals 1 2.5% of the time). 86% of evergreen or mixed forest grid cells in the study area never received a fuels reduction treatment. 2.0% of grid cells were treated 3 or more times. Out of the 1,445,779 grid cells, 536,711 are mixed forest or evergreen forest.

Table 2: Descriptive statistics for WUI block data set

	All obs. (mean)	Obs. within 5 km threshold (mean)
Distance to nearest fire in study period (km)	15.4	14
Population*	4,948	4,660
No. of housing units*	2,197	2,460
Per capita income*	21,361	21,182
Percent graduated high school*	83.8	86.5
Number of observations	454,767	105,613

*Variable is observed only at the Census tract level.

Table 3: Main specification predicting fuels reduction status of forested grid cells conditional on whether nearby WUI Census blocks experienced recent wildfires

	(1)	(2)	(3)	(4)	(5)
fireclose_t	0.0161	0.0182	0.0161	0.0167	0.0163
	(0.0038)**	(0.0039)**	(0.0037)**	(0.0042)**	(0.0041)**
	(0.0048)**	(0.005)**	(0.0043)**	(0.0053)**	(0.0051)**
fireclose_{t-1}	0.0074	0.0081	0.006	0.0058	0.0085
	(0.0032)*	(0.0024)**	(0.0025)*	(0.0027)*	(0.0033)*
	(0.0043)	(0.0031)**	(0.0028)*	(0.0031)	(0.0043)*
fireclose_{t-2}	0.0044	0.0058	0.0018	0.0051	0.0040
	(0.0032)	(0.0029)*	(0.0025)	(0.0033)	(0.0029)
	(0.0035)	(0.0032)	(0.0025)	(0.0035)	(0.0031)
fireclose_{t-3}	0.0001	0.0004	0.0011	0.0011	0.0005
	(0.0033)	(0.0029)	(0.0033)	(0.0035)	(0.0029)
	(0.0029)	(0.0024)	(0.0028)	(0.0025)	(0.0025)
fireclose_{t-4}	-0.0008	-0.0015	-0.0008	-0.0001	-0.0009
	(0.0025)	(0.0025)	(0.0027)	(0.0027)	(0.0025)
	(0.0025)	(0.0028)	(0.0025)	(0.0027)	(0.0023)
Fixed effects	Year	Year×unit	Year×district	Year×county	Year×tract
No. of groups	207,175	207,175	207,175	207,175	207,175
No. of obs.	1,864,575	1,864,575	1,864,575	1,864,575	1,864,575

Note: Regressions include grid cells within 5 km of any WUI Census block. Variables $\text{fireclose}_{t-\ell}$ equal 1 if a fire occurred within 5 kilometers of a nearby Census block in year $t-\ell$ and 0 otherwise. The sample is limited to pixels NLCD classifies as forested in 2006. In addition to fixed effects noted in the table, all models include grid cell fixed effects. Robust standard errors are clustered by district first and unit second, ** p<0.01, * p<0.05.

Table 4: Test of robustness in which the dependent variable is recoded in order to examine the influence of multi-year fuels reduction projects

	(1)	(2)	(3)	(4)	(5)
fireclose_t	0.0155	0.0171	0.0162	0.0164	0.0159
	(0.0036)**	(0.0038)**	(0.0036)**	(0.004)**	(0.0039)**
	(0.0045)**	(0.0047)**	(0.0039)**	(0.0049)**	(0.0047)**
fireclose_{t-1}	0.0072	0.0071	0.0058	0.0056	0.0080
	(0.003)*	(0.0022)**	(0.002)**	(0.0024)*	(0.0032)*
	(0.0041)	(0.003)*	(0.0022)**	(0.0029)	(0.0043)
fireclose_{t-2}	0.0036	0.005	0.002	0.0047	0.0032
	(0.0026)	(0.0024)*	(0.0023)	(0.0028)	(0.0024)
	(0.0026)	(0.0027)	(0.0022)	(0.0027)	(0.0024)
fireclose_{t-3}	-0.0008	-0.0004	0.0011	0.0001	-0.0007
	(0.0027)	(0.0024)	(0.0028)	(0.0029)	(0.0025)
	(0.0024)	(0.0022)	(0.0023)	(0.0022)	(0.0023)
fireclose_{t-4}	-0.0012	-0.0017	-0.0004	-0.0007	-0.0019
	(0.002)	(0.0022)	(0.0024)	(0.0022)	(0.0023)
	(0.002)	(0.0022)	(0.0021)	(0.0022)	(0.002)
Fixed effects	Year	Year×unit	Year×district	Year×county	Year×tract
No. of groups	207,175	207,175	207,175	207,175	207,175
No. of obs.	1,864,575	1,864,575	1,864,575	1,864,575	1,864,575

Note: Regressions include grid cells within 5 km of any WUI Census block. Variables $\text{fireclose}_{t-\ell}$ equal 1 if a fire occurred within 5 kilometers of a nearby Census block in year $t-\ell$ and 0 otherwise. The sample is limited to pixels NLCD classifies as forested in 2006. In addition to fixed effects noted in the table, all models include grid cell fixed effects. Robust standard errors are clustered by district first and unit second, ** p<0.01, * p<0.05.

Table 5: Placebo test in which two-year leads of *fireclose* are included in order to rule out joint determination of fire and fuel reduction project locations

	(1)	(2)	(3)	(4)	(5)
fireclose_t	0.0176	0.0204	0.0182	0.0188	0.0190
	(0.0045)**	(0.0048)**	(0.004)**	(0.0051)**	(0.0049)**
	(0.0059)**	(0.0063)**	(0.0049)**	(0.0065)**	(0.0062)**
fireclose_{t-1}	0.0105	0.0104	0.0084	0.0085	0.0117
	(0.0036)**	(0.0029)**	(0.003)**	(0.003)**	(0.0038)**
	(0.0049)*	(0.0035)**	(0.0032)**	(0.0035)*	(0.005)*
fireclose_{t-2}	0.0088	0.01	0.0041	0.0098	0.0081
	(0.0041)*	(0.0037)**	(0.0033)	(0.0042)*	(0.0039)*
	(0.0045)	(0.004)*	(0.0033)	(0.0044)*	(0.0043)
fireclose_{t-3}	0.0043	0.0037	0.0028	0.0051	0.0053
	(0.0041)	(0.0036)	(0.0039)	(0.0043)	(0.0038)
	(0.0033)	(0.0028)	(0.003)	(0.0029)	(0.0032)
fireclose_{t-4}	-0.0007	-0.0014	-0.0002	0.0004	-0.0002
	(0.003)	(0.003)	(0.0032)	(0.0032)	(0.0028)
	(0.0028)	(0.003)	(0.0029)	(0.0029)	(0.0028)
fireclose_{t+1}	0.0027	0.0042	0.0026	0.0026	0.0026
	(0.0027)	(0.0028)	(0.003)	(0.0028)	(0.0029)
	(0.0025)	(0.0028)	(0.0029)	(0.0027)	(0.0028)
fireclose_{t+2}	0.0039	0.0071	0.0058	0.0047	0.0062
	(0.0029)	(0.0031)*	(0.0036)	(0.0031)	(0.0031)*
	(0.0031)	(0.0036)*	(0.0041)	(0.0031)	(0.0035)
Fixed effects	Year	Year×unit	Year×district	Year×county	Year×tract
No. of groups	207,175	207,175	207,175	207,175	207,175
No. of obs.	1,450,225	1,450,225	1,450,225	1,450,225	1,450,225

Note: Regressions include grid cells within 5 km of any WUI Census block. Variables $\text{fireclose}_{t-\ell}$ equal 1 if a fire occurred within 5 kilometers of a nearby Census block in year $t-\ell$ and 0 otherwise. The sample is limited to pixels NLCD classifies as forested in 2006. In addition to fixed effects noted in the table, all models include grid cell fixed effects. Robust standard errors are clustered by district first and unit second, ** p<0.01, * p<0.05.

Table 6: Base specification with observations within the perimeter of previous fires removed to avoid misclassification of post-fire activities as fuels reductions

	(1)	(2)	(3)	(4)	(5)
fireclose_t	0.0121	0.0139	0.0115	0.0125	0.0125
	(0.0032)**	(0.0034)**	(0.0035)**	(0.0036)**	(0.0035)**
	(0.0039)**	(0.0042)**	(0.0039)**	(0.0044)**	(0.0041)**
fireclose_{t-1}	0.0031	0.0049	0.004	0.0031	0.0038
	(0.0028)	(0.0025)*	(0.0027)	(0.0028)	(0.0025)
	(0.0033)	(0.0028)	(0.0028)	(0.0029)	(0.0027)
fireclose_{t-2}	0.0033	0.0042	-0.0001	0.0037	0.0028
	(0.0035)	(0.003)	(0.0025)	(0.0036)	(0.0031)
	(0.0036)	(0.0032)	(0.0024)	(0.0036)	(0.0031)
fireclose_{t-3}	-0.0021	-0.0009	0.0000	-0.0006	-0.0018
	(0.0034)	(0.003)	(0.0033)	(0.0036)	(0.0029)
	(0.0029)	(0.0025)	(0.0028)	(0.0028)	(0.0025)
fireclose_{t-4}	-0.0006	-0.0011	-0.0008	0.0003	-0.0007
	(0.0026)	(0.0027)	(0.0028)	(0.0027)	(0.0029)
	(0.0026)	(0.0028)	(0.0027)	(0.0028)	(0.0024)
Fixed effects	Year	Year×unit	Year×district	Year×county	Year×tract
No. of groups	200,895	200,895	200,895	200,895	200,895
No. of obs.	1,770,739	1,770,739	1,770,739	1,770,739	1,770,739

Note: Regressions include grid cells within 5 km of any WUI Census block. Variables $\text{fireclose}_{t-\ell}$ equal 1 if a fire occurred within 5 kilometers of a nearby Census block in year $t-\ell$ and 0 otherwise. The sample is limited to pixels NLCD classifies as forested in 2006, and pixels within the perimeter of previous fires have been removed. In addition to fixed effects noted in the table, all models include grid cell fixed effects. Robust standard errors are clustered by district first and unit second, ** p<0.01, * p<0.05.

Table 7: Variation in salience effects by census block characteristics

	(1) Population	(2) Housing units	(3) Ln(Fire size)	(4) VCC
I. Interaction coefficient	1.1e-06	2.9e-06	.0011	-.0041
	(5.4e-07)*	(9.8e-07)**	(.00099)	(.0036)
II. Interaction coefficient	1.1e-06	2.9e-06	.0011	
	(5.4e-07)*	(9.8e-07)**	(.00099)	
VCC	.00068	.00065	.0012	
	(.00056)	(.00056)	(.00054)*	
Grid cells within past fire perimeters	Yes	Yes	No	Yes
No. demog. interaction lags	4	4	4	4
No. of groups	207,175	207,175	200,895	207,175
No. of obs.	1,864,575	1,864,575	1,770,739	1,864,575
F-statistic	0.3611	1.2714	0.2721	0.8673
Mean	4,949	2,359	8.96	2.38
Min	0	1	7.01	1.01
Max	36,146	9,905	12.4	3.86

Note: Regressions are as in column 3 of table 3, but include interaction terms as specified in equation 10, whose coefficients are reported. Row II also includes a control for vegetation condition class (VCC), whose coefficient is reported. Robust standard errors are clustered by unit, ** p<0.01, * p<0.05. Reported F-statistics use results from an unreported regression to test the null hypothesis that estimated ζ coefficients from regressions in row I are equal across lags of the interaction. An F-statistic less than 3.00 indicates insufficient evidence that ζ coefficients differ among lags. The reported mean, maximum, and minimum in each column correspond to sample statistics for each each column's variable (z_s) among all treated blocks.