Do Fuel Treatments Mitigate the Cost of Wildfires? Evidence from the Northwest Forest Plan

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October 22, 2024

Abstract

Increases in the size and severity of wildfires have resulted in significant economic costs and damages in recent decades. This study explores the degree to which fuel treatments, commonly promoted by fire ecologists as a means of restoring forest health, reduce the size and cost of fighting wildfires. We investigate fires igniting on U.S. Forest Service land in the Pacific Northwest between 2006 and 2023, leveraging exogenous variation in fuel treatments arising from a system of protected areas designed to conserve the northern spotted owl, old growth forest, and other endangered species. We find that fires starting in the protected areas are less likely to occur close to fuel treatments and are more costly to suppress, on average. Conservative back-of-the-envelope estimates suggest that three to five dollars are saved in fire suppression costs for every dollar spent on fuel treatments. We also find that fuel treatments do reduce fire size, though this effect is attenuated by the endogenous allocation of fire suppression effort away from fires intersecting with fuel treatments. Our results suggest that environmental protections have increased the public burden of fighting wildfires and placed the species they were intended to protect at greater risk from wildfire. Taken together, these findings highlight the potential for reforming environmental protections to achieve both economic savings and conservation benefits.

"You own the fuel, you own the fire"
Urban fire specialist's adage

1 Introduction

In May 2001, U.S. governmental officials were alarmed to detect a mysterious aerosol signature in the form of a smoke plume in Central Alberta, Canada. The signal was so extreme that U.S. government officials called the Canadian government to ask if a nuclear device had been detonated. The source was not a bomb, but a wildfire, the Chrisholm Fire, which at its peak seven-hour run, released the energy equivalent of four Hiroshima bombs per minute (Vaillant, 2023). Fires of this size are known to create their own weather systems with hurricane-force winds and lightning that ignite more fires many miles away. This is just a glimmer of the frightening intensity and destructive capability of wildfires in the 21st century.

As the size and severity of wildfires have increased in recent decades (Miller et al., 2009), so too have the economic costs and damages, with the estimated total annual cost in the U.S. ranging from $394-893 billion USD (JEC, 2023). Wildfires incur economic costs through various channels, such as losses in human-made and natural assets (Bayham et al., 2022; Wang and Lewis, 2024), fire suppression costs (Baylis and Boomhower, 2023), human health (Molitor et al., 2023; Heft-Neal et al., 2023), labor market impacts (Borgschulte et al., 2022), and losses in ecosystem services (Smith, 1993). Such costs are expected to rise across the globe with climate change (Abatzoglou and Williams, 2016), increasing development in the wildland-urban interface (WUI) (Radeloff et al., 2018), and fire exclusion policies (Schoennagel et al., 2017).

The build-up of combustible material, or fuel loads, in forests is one of the leading causes of increasing wildfire severity (Miller et al., 2009). Fuel loads have built up over time far beyond their natural carrying capacity in response to current and historical fire suppression policies (Stephens et al., 2007; North et al., 2022). Fuel treatment activities, such as prescribed fires or mechanical tree removal, reduce fuel loads and have the potential to significantly alter the economic costs of wildfires. However, despite widespread consensus in the forest ecology literature that fuel treatments are effective at reducing wildfire severity, they have been strikingly underemployed in the Western U.S. (Agee and Skinner, 2005; Kolden, 2019).

Fuel treatments may be underemployed because public agencies are chronically underfunded and face contradicting expectations from the public. For example, the United States Forest Service (USFS) employs less than 30,000 people despite owning more than 193 million acres of public land.[1] Public pressure and risk aversion skew an already scarce resource base towards fire suppression at the expense of fuel treatments to avoid public lawsuits and condemnation. Regulatory constraints based on other environmental objectives, such as endangered species protections, federal and state

[1]Unlike the Eastern U.S., public lands in the Western U.S. comprise of the majority of forest land and burned area from wildfires. For example, in the Pacific Northwest federally managed lands accounted for around 68% of the total burned area footprint from 1984-2018 (Barros et al., 2021).

air quality standards, survey and manage protocols, wilderness areas, and the NEPA process, significantly hinder the ability of public agencies to conduct fuel treatments on public lands (North et al., 2012, 2015; Edwards and Sutherland, 2022). Environmental regulations such as these lead to instances where the costs associated with no action are overlooked, and the "precautionary principle" becomes the "paralyzing principle" (Hessburg et al., 2021).

This paper presents the first empirical, causally identified estimate of the effectiveness of fuel treatments in reducing wildfire costs. Although prior forest ecology research has demonstrated the effectiveness of fuel treatments in reducing fire severity (Agee and Skinner, 2005; Kolden, 2019), quantifying their economic benefits remains limited (Kline, 2004).[2] Despite calls for the widespread adoption of these practices as a means to reduce economic costs (USFS and State of California, 2020; State of California, 2021), the existing economic literature has focused more on identifying the determinants of fuel treatment activity and fire suppression efforts rather than the relationship between the two (Plantinga et al., 2022; Baylis and Boomhower, 2023; Bayham and Yoder, 2020; Wibbenmeyer et al., 2019; Anderson et al., 2023). In this study, we investigate how fuel treatments can mitigate the economic costs of wildfires by assessing their impact on two key factors: fire size and suppression costs.[3] By analyzing fires igniting on United States Forest Service (USFS) land in the Pacific Northwest from 2006 to 2023, we find evidence that fuel treatments effectively reduce the economic costs and damages associated with wildfires.

The lack of research linking fuel treatment activities' impact on economic outcomes is likely due to the environmental and spatial-temporal complexities of wildfires, fuel treatments, and fire suppression efforts, resulting in at least two empirical challenges in identifying the causal effects of fuel treatments. First, the location and extent of fuel treatments and fire suppression efforts are jointly determined by socio-economic and environmental factors (Plantinga et al., 2022; Baylis and Boomhower, 2023; Bayham and Yoder, 2020; Wibbenmeyer et al., 2019; Anderson et al., 2023). Consequently, estimation strategies that compare fires or areas with varying levels of adjacent and or intersecting areas of fuel treatments are likely to suffer from simultaneity bias, often resulting in findings of small to zero impacts (Sánchez et al., 2019; Yoder and Ervin, 2012). Second, even if fuel treatments are conducted exogenously, the endogenous allocation of suppression effort across fires mediates the effect of fuel treatments on the size and cost of suppressing a fire. As we demonstrate in our conceptual framework, fuel treatments could actually increase the size and suppression cost of nearby fires, even if they collectively decrease the size and costs of all fires.[4] Thus, comparing fires adjacent to fuel treatments to those that are not may not provide an accurate assessment of the overall benefits associated with fuel treatments.

We address the empirical challenges of identifying the economic benefits of fuel treatments

[2]Previous studies have focused on the cost-effectiveness of fuel treatments in reducing high-severity fires (Hartsough et al., 2008). Research on economic benefits, however, has relied on fire simulations (Taylor et al., 2015; Thompson et al., 2013b) or meta-analyses of individual case studies (Hjerpe et al., 2024; Hunter and Taylor, 2022) to assess the economic impact of fuel treatments.

[3]According to the National Interagency Fire Center, federal agencies spent $55 billion (2017) on wildfire suppression from 1985 to 2022, with a total of 211 million acres burned, not including state and local suppression efforts.

[4]Rideout et al. (2008) derives a similar result using a similar model of fuel treatments and fire suppression effort.

in the following ways. First, we employ an instrumental variable (IV) strategy that exploits exogenous variation in fuel treatments arising from spatial variation in protected areas, specifically late-successional reserves (LSRs) established under the Northwest Forest Plan (NWFP). These protected areas were designed to protect the northern spotted owl, listed under the endangered species act (ESA), but have had the unintended consequence of restricting fuel treatment activity within such areas because of increased management restrictions and litigation potential from environmental groups (Johnson et al., 2023). Spatial variation in protected areas generates quasi-random variation in fuel treatment activity because their boundaries were established based on the nesting, roosting, foraging, and dispersal habits of the northern spotted owl, as well as the ecological needs of other endangered species and riparian habitats (Gaines et al., 2022; Johnson et al., 2023). Second, using a stylized model of fire suppression effort allocation, we derive a sufficient condition under which fuel treatments generate overall economic benefits, considering both wildfire damages and suppression costs. We demonstrate that a negative effect of fuel treatments on fire size and suppression costs is sufficient evidence that fuel treatments accrue collective economic benefits across all fires.

We find that fires igniting in protected areas are less likely to occur close to fuel treatments and are more costly to suppress on average, demonstrating that fuel treatments significantly reduce the cost of suppressing wildfires. We do not find a statistically significant impact of fuel treatments on fire size; however, our model of fire suppression effort allocation suggests that this is due to the endogenous reallocation of suppression resources away from fires that ignite near treated areas. Applying a bootstrap intersection-union hypothesis test to our sufficient condition, we find evidence that fuel treatments have a direct effect on reducing fire sizes and provide overall economic gains. Building on this evidence, we estimate the counterfactual economic benefits from reduced suppression costs that would have been realized had the size of all fuel treatments in our sample period been proportionally larger. Our conservative back-of-the-envelope calculations suggest that for every dollar spent on fuel treatments, three to five dollars are saved in fire suppression costs, depending on the level of increased treatment activity. These results indicate that fuel treatments are a cost-effective strategy for mitigating wildfire risks.

Land managers and fire ecologists have long acknowledged the unintended effects of the NWFP reserves on fuel treatment and wildfire activity in the Pacific Northwest (Spies et al., 2019; Hessburg et al., 2021). Previous studies have shown that increasing areas of high-severity fire have been the leading cause of loss in northern spotted owl habitat (Davis et al., 2016) and old-growth forests (Davis et al., 2015) since the NWFP's inception. Others have pointed out the conflicting incentives of land managers under the ESA due to fuel treatments' short-term negative impacts on northern spotted owl habitat (Spies et al., 2018; North et al., 2012). The present study contributes to this literature by estimating the magnitude by which these policies have hampered fuel treatment activity in the region and how this has translated into increasing the public burden of fighting wildfires. Our first-stage results confirm that fires in protected areas are less likely to be near fuel treatments, while reduced-form results demonstrate that fires igniting in protected areas have significantly higher costs than those igniting outside of protected areas, on average.

The present study contributes to the economic literature on natural disasters. The literature has emphasized the government's role in bearing the cost of protection from natural disasters, which has led to an unintended increase in development in high-risk areas (Kousky et al., 2006; Boustan et al., 2012; Baylis and Boomhower, 2023; Troy, 2007). Property insurance has the potential to protect individuals from the financial impacts of natural disasters (Busby et al., 2013; Kousky, 2019). However, risk information asymmetries and the infrequent, catastrophic, and spatially correlated nature of natural disasters create significant challenges for insurance markets to adapt to their escalating risk (Wagner, 2022a,b; Boomhower et al., 2024). Moreover, damages to private property are just one element of the costs associated with natural disasters. Indeed, previous work demonstrates that the most significant costs of natural disasters can accrue through indirect channels, such as exposure to smoke from wildfires, many of which ignite on public land.[5] This has led policymakers to seek cost-effective investments to mitigate natural disaster risks, including mandating fire-resilient building codes for new homes built in California (Baylis and Boomhower, 2021). We contribute to this literature by demonstrating that public investments in natural capital can be a cost-effective means of protection from natural disasters.

Our study also contributes to the literature on environmental protections and climate change adaptation by examining how ancillary environmental regulations impact wildfire management and fuel treatment activities. We demonstrate that conflicting environmental policies—such as those aimed at protecting endangered species—can unintentionally hinder critical climate adaptation strategies, like fuel treatments. The growing literature on climate adaptation has focused on private responses (Barreca et al., 2016; Burke and Emerick, 2016; Auffhammer, 2022; Hashida and Lewis, 2019), while the environmental protection literature emphasizes the impact of protections on private land values, land use, and the labor market (Maximilian Auffhammer et al., 2020; Nelson et al., 2017; Ferris and Frank, 2021). Our study fills this gap by exploring the role of public investments and by highlighting the need for policy reform to reconcile conflicting environmental objectives in the face of climate change.

Finally, we contribute to the literature on climate change by illustrating the capability of investments in ecosystem health as a cost-effective means of mitigating the impacts of climate change. The climate literature has emphasized investments in man-made capital or changes in crop choice as the primary margin of adaptation with little consideration of investments in ecosystem health (Gerlagh and van der Zwaan, 2002; Deschênes and Greenstone, 2007; Hashida and Lewis, 2019; Baylis and Boomhower, 2021). We demonstrate that investments in ecosystem health can play an equally important role in mitigating the economic costs posed by climate change, particularly in fire-prone regions.

The paper is organized as follows: Section 2 provides a brief overview of wildland fire institutions and fuel treatments along with background of the Northwest Forest Plan. Section 3 establishes a simple model of fuel treatment and fire suppression effort to motivate our empirical approach and

[5]For example, Borgschulte et al. (2022) estimate a $125 billion/year reduction in quarterly earnings due to smoke exposure.

inform the interpretation of our estimates. Section 4 provides an overview of our research design and Section 4.1 discusses the data. Section 5 estimates the marginal effect of fuel treatment on fire suppression costs along with robustness checks (Section 5.1). Section 5.2 explores the counterfactual benefits of increased fuel treatment activity in our sample and Section 6 concludes.

2 Background

2.1 Fighting Fire with Fire: Wildland Firefighting & Fuel Treatments in the Western U.S.

The Great Fire of 1910, an apocalyptic blaze that burned 3 million acres in 2 days in Washington, Idaho, and Montana, marked an important turning point in the management of U.S. national forests (Egan, 2011). Only five years after its founding, the USFS was severely underfunded and under political threat of dismantling.[6] However, the heroic deeds of forest service rangers along with the shock and terror from the fire dramatically changed the public perceptions of the USFS, ultimately leading to the USFS's expansion and a major shift in its mission statement: from prioritizing conservation to fighting forest fires. Prioritizing wildfire suppression led to the "10 a.m." policy instituted by the USFS in 1935, which stated the goal to successfully contain any fires by 10 a.m. the day following its initial report (Loveridge, 1944).

Shortly thereafter, other federal, state, and local government agencies followed in the USFS's footsteps to implement similar wildfire suppression policies (Pyne, 2008). A wildfire's ignition location and geographic extent broadly determine the financial and operational responsibility for suppressing a wildfire (Hoover and Lindsay, 2017), with the nearest fire management authority usually attempting to quickly extinguish it in what is known as the "initial attack." For example, the primary responsibility for fires igniting on National Forest land rests with the USFS. In contrast, the state is responsible for fires starting in unincorporated private land (e.g., CAL FIRE in California). When wildfires are large enough to affect multiple agencies and jurisdictions, local Emergency Operation Centers and multi-agency coordinating groups facilitate the sharing of information, objectives, and the allocation of resources between agencies.

Successful wildfire suppression by federal, state, and local government agencies has unintentionally led to increased fuel loads that are in marked disequilibrium with the underlying ecological template across much of the western U.S. (North et al., 2022). For example, 5-12% of California burned annually pre-1800, a large portion of which occurred through cultural indigenous burning (Stephens et al., 2007). Indeed, it is an often-repeated mantra that the major ecological issue facing western forests today is the relative absence of fire, which is in direct conflict with popular information campaigns like "Smoky the Bear" that emphasize wildfire suppression (Miller, 2007).

Fuel treatments, such as prescribed fires or mechanical tree removal, aim to return forest ecosystems to their more natural state by emulating the natural processes of low-severity fires by reducing

[6] For example, one forest service ranger working at poverty level wages was the sole employee responsible for over 300,000 acres of land (Egan, 2011).

fuel loads, maintaining open stands of trees, and eliminating shade-tolerant species of trees that are more susceptible to wildfire. Because such ecosystems are adapted to frequent low-severity fires, forests that receive such fuel treatments experience fewer high-severity wildfires and thus enhance the ecosystem services associated with such forests through reduced smoke exposure, increased nutrient cycling, water quality, and carbon sequestration post-wildfire, along with the promotion of biodiversity (Murphy et al., 2007; Converse et al., 2006; Boerner et al., 2009; Finkral and Evans, 2008; Yocom Kent et al., 2015; Richter et al., 2019).

Although there is no rigorous causal evidence directly linking fuel treatments to reductions in fire suppression costs, both qualitative and fire simulation evidence suggests that fuel treatments help decrease these costs by reducing the size and severity of wildfires (Romero and Menakis, 2013; Thompson et al., 2013b). Fuel treatments can enhance the effectiveness of both "direct" and "indirect" firefighting efforts, which likely contributes to cost savings (Romero and Menakis, 2013). Direct attack involves firefighting actions performed near the fireline, such as constructing control lines, smothering flames, or applying water or chemical retardants. These efforts are only feasible when wildfires have sufficiently low flame lengths—a condition that fuel treatments help create. Indirect attack, on the other hand, consists of operations conducted at some distance from the fire's perimeter. This may involve using fuel breaks or creating firelines where combustible material is removed to halt a fire's progression.[7]

By increasing the effectiveness of direct and indirect attacks, fuel treatments reduce reliance on the more costly aerial attack methods, which involve applying water or chemical retardant via helicopters or fixed-wing aircraft. Aerial attacks require significant capital investment and are considerably more expensive than ground-based suppression tactics (Calkin et al., 2014; Thompson et al., 2013a; Stonesifer et al., 2021).

2.2 The Northwest Forest Plan Reserve System

It is said that when President Jimmy Carter was on his way to view the devastation caused by the eruption of Mt. St. Helens in 1980, he expressed horror at the sight of a shaven landscape. State officials had to gently explain that what Carter saw was clear-cut logging and not the aftermath of the explosion (Dietrich, 2010). The emotion brought about by the sight of clear-cuts and their deleterious effects on ecosystems led to one of the most hotly contested public debates: What should be the management objectives of federal forest owners? The northern spotted owl (NSO) was the centerpiece of this debate. It became not only a symbol for old-growth forest preservation but also the legal basis from which federal forest owner objectives changed through the ESA. The debate culminated in the early 1990s, and within only five years, federal forests in the Pacific Northwest underwent a sudden and tremendous shift in management focus from providing sustained yield timber to conserving biodiversity with emphasis on endangered species (Thomas et al., 2006).

[7] Fuel treatments also facilitate "back-burning," a form of indirect attack where fire is deliberately set to reduce fuel ahead of the wildfire. Typically, back-burning requires favorable wind conditions, but fuel treatments lessen the reliance on such conditions by proactively removing fuel before a fire occurs.

After listing the NSO as threatened by the U.S. Fish & Wildlife Service (USFWS), 6.9 million acres of federal forest were designated as critical habitat in 1992, encompassing parts of Washington, Oregon, and northern California. The Clinton administration subsequently initiated the Northwest Forest Plan (NWFP) in 1994, establishing a system of reserves over 24.4 million acres of federal forest land aimed at conserving old-growth habitats, NSO populations, and essential watersheds and riparian zones. This plan is one of the largest temperate forest reserve system in the world (Gaines et al., 2022; Spies et al., 2018).

During the formulation of the NWFP, the Clinton administration faced stark trade-offs between timber production and species conservation (Johnson et al., 2023). Various reserve options were presented, each proposing different protections for "working" forest lands—those deemed productive for timber harvest (Johnson et al., 2023). The final plan represented a compromise, establishing late-successional reserves (LSRs) based on the nesting, roosting, foraging, and dispersal habits of the NSO and the ecological needs of other endangered species. Ultimately, 7.4 million acres were designated as LSRs and approximately 4 million acres as Matrix lands, which are less restricted and intended for timber production (Figure 1). Notably, Matrix areas included about 2 million acres of late-successional/old-growth forest compared to the 3.7 million acres preserved in LSRs (Johnson et al., 2023).[8]

Despite recognizing the importance of active management in dry forests, the NWFP has unintentionally restricted fuel treatment activities due to conservative interpretations of its rules and the potential for litigation from environmental groups (Johnson et al., 2023). Coupled with a century of active fire suppression, forested areas within LSRs have experienced significant changes due to fuel build-up, particularly in dry forests east of the Cascade Mountain Range, which are more vulnerable to wildfires than their wet counterparts to the west (Reilly et al., 2018).[9] Conversely, the less-restricted Matrix areas allow for more intensive timber harvests and silvicultural activities, resulting in significantly more acres of fuel treatment compared to LSR areas. This disparity underscores the significant differences in the spatial distribution of fuel treatments across national forests in the Pacific Northwest (Figure 2a).

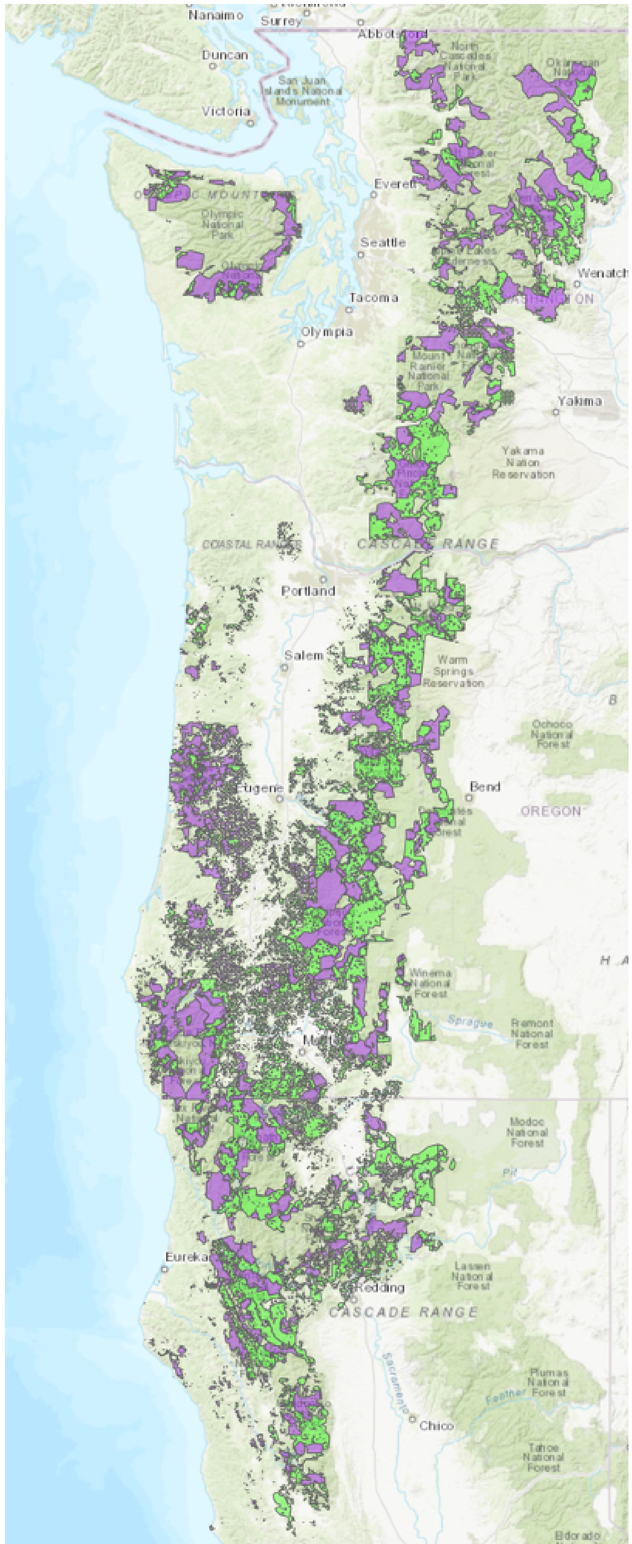
3 Conceptual Framework

In this section, we present a stylized model to identify the mechanisms through which fuel treatments influence fire size and suppression costs and to clarify the main empirical challenges we face in identifying and interpreting such effects. The model illustrates how the effect of fuel treatments is mediated by the endogenous response of a fire manager as they allocate suppression effort across

[8]While LSRs aimed to protect the NSO, they do not always coincide with the critical habitat designated by the USFWS. For instance, around 40% of the critical habitat designated in 2012 is located within Matrix areas in Eastern Washington (Gaines et al., 2010).

[9]Dry forests historically experienced frequent wildfires, while wet forests faced wildfires every one to four hundred years (Johnson et al., 2023). Given these systematic differences, some scientists have criticized the inclusion of dry forests in the NWFP reserve system (Gaines et al., 2022). In response, the NWFP included provisions to encourage active management in LSRs to restore dry-zone forests to a more natural state.

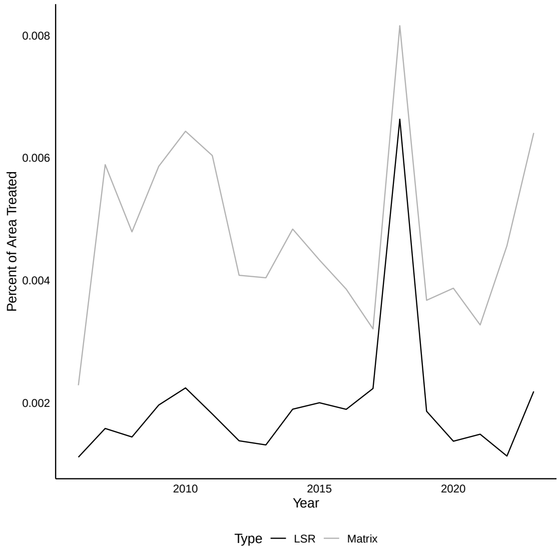
Figure 1: Distribution of Matrix and LSR land designations in the Northwest Forest Plan area



Matrix areas are shaded in bright green, LSRs in purple, and national forests in light green

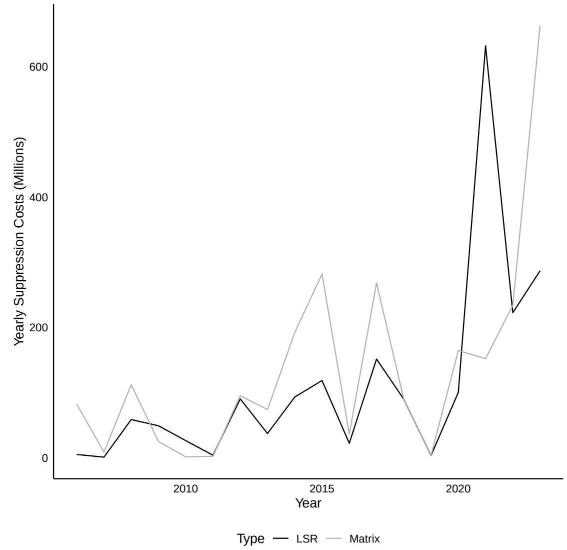
Figure 2: Trends in Fuel Treatments & Fire Suppression Costs in Matrix & LSRs

(a) Fuel Treatments



"Percent of Area Treated" is the total annual acres of fuel treatment divided by the total area of Matrix or LSR areas.

(b) Fire Suppression Costs



Suppression costs are adjusted for inflation and are in terms of 2020 USD

fires. In turn, the model explains why fuel treatments may or may not reduce the size or suppression cost of a nearby fire, even if they reduce the total acres burned and suppression costs across all fires. We use the model to derive a sufficient condition under which fuel treatments collectively provide economic benefits across all fires, resulting in a testable hypothesis that informs our empirical framework.[10]

3.1 Setup

A fire manager allocates fire suppression effort E_i toward fighting $i = 1, \ldots, N$ fires burning simultaneously, conditional on an existing distribution of fuel treatments across the landscape. We assume that a fire manager's objective is to minimize expected losses, which are equal to the sum of expected damages and fire suppression costs, subject to a resource constraint on suppression effort.[11] The fire manager's problem can be expressed as:

$$\max_{E_1,\ldots,E_N} -\sum_{i=1}^{N} \left[L(X_i) \cdot S(E_i, F_i) + C(E_i)\right] \quad \text{s.t.} \quad \sum_{i=1}^{N} E_i \leq \bar{E},$$

where F_i denotes the volume of fuel treatments near fire i. For simplicity, we assume suppression costs $C(E_i)$ are the same across fires, conditional on effort. We also assume that resources move

[10] All derivations of our results can be found in Appendix A.

[11] This is a version of the "least cost plus loss" model, which has been used to model fire manager behavior for many economic fire suppression models (Donovan and Rideout, 2003). More general models provide similar, yet more nuanced, insights on the tradeoffs facing a fire manager (e.g., Bayham and Yoder, 2020).

from cheaper sources (e.g., hand crews) to more expensive sources (e.g., dozers and air tankers) as effort is expanded, resulting in a suppression cost function that is increasing and convex in effort. Expected fire damages are assumed to be linear in expected fire size $S(E, F)$, which is assumed to be decreasing and convex in effort and fuel treatments due to diminishing returns. $L(X_i)$ represents the constant loss associated with a one-unit increase in fire size, which is a function of assets-at-risk, X_i.

The necessary and sufficient conditions associated with a fire manager's effort allocation, E_i^*, are:

$$-L(X_i)\frac{\partial S_i(E_i^*, F_i)}{\partial E_i} = \frac{\partial C(E_i^*)}{\partial E_i} + \lambda \quad \forall i \in \{1, ..., N\}$$
$$\lambda \cdot \left(\sum_{i=1}^{N} E_i^* - \bar{E}\right) = 0,$$

where λ denotes the Lagrange multiplier associated with the resource constraint. The first-order conditions reflect that the marginal benefit of allocating one unit of effort to suppress a fire, in terms of the foregone damages, must be equal to its marginal suppression cost and the shadow cost of effort for E_i^* to be optimal. They also reflect the equi-marginal principle: effort is optimally allocated across fires when the marginal net benefit of effort is equal across all fires. Further, the first-order conditions demonstrate that more suppression effort will be devoted to fires with higher levels of assets-at-risk (Plantinga et al., 2022; Baylis and Boomhower, 2023).

3.2 The Impacts of Fuel Treatments

We are ultimately interested in understanding how fire suppression effort, costs, and fire size respond to differences in the volume of nearby fuel treatments close to an ignitions. The results depend on whether fuel treatments and fire suppression effort are q-complements or q-substitutes (Hicks, 1970). Specifically, fuel treatments and fire suppression effort are q-substitutes if an increase in fuel treatments *decreases* the marginal productivity of suppression effort on fire size, which can be expressed formally as $-\frac{\partial^2 S(E,F)}{\partial F \partial E} < 0$.[12] Intuitively, if fuel treatments increase the marginal productivity of suppression effort, a fire manager will reallocate effort toward fires with nearby fuel treatments until the marginal benefit is equal to its marginal cost (including the shadow cost of effort if the resource constraint is binding). The opposite is true if fuel treatments decrease the marginal productivity of suppression effort. This result has implications for fuel treatments' effects on suppression costs and fire size.

[12] Note that since $\frac{\partial S(E,F)}{\partial E} < 0$, we can characterize the marginal benefit of suppression effort as $-L(X) \cdot \frac{\partial S(E,F)}{\partial E}$. Hence, we write the effect of fuel treatments on the marginal productivity of suppression effort using the cross-partial elasticity with a negative.

Result 1. Fuel treatments will decrease fire suppression effort if and only if fuel treatments and suppression effort are q-substitutes:

$$\frac{dE_i^*}{dF_i} < 0 \iff -\frac{\partial^2 S(E_i, F_i)}{\partial F_i \partial E_i} < 0.$$

The opposite is true if fuel treatments and suppression effort are q-complements.

Corollary 1.1. Fuel treatments will decrease fire suppression costs if and only if fuel treatments and suppression effort are q-substitutes.

$$\frac{dC(E_i^*)}{dF_i} = \frac{dC(E_i^*)}{dE_i} \cdot \frac{dE_i^*}{dF_i} < 0 \iff \frac{dE_i^*}{dF_i} < 0 \iff -\frac{\partial^2 S(E_i, F_i)}{\partial F_i \partial E_i} < 0.$$

The opposite is true if fuel treatments and suppression effort are q-complements.

Corollary 1.2. Fuel treatments will decrease fire size if fuel treatments and suppression effort are q-complements.

$$\frac{dS(E_i^*, F_i)}{dF_i} = \frac{\partial S(E_i^*, F_i)}{\partial E_i} \cdot \frac{dE_i^*}{dF_i} + \frac{\partial S(E_i^*, F_i)}{\partial F_i} < 0 \iff \frac{dE_i^*}{dF_i} > 0 \iff -\frac{\partial^2 S(E_i, F_i)}{\partial F_i \partial E_i} > 0.$$

In contrast, fuel treatments may or may not decrease fire size if fuel treatments and suppression effort are q-substitutes.

Corollary 1.1 is a direct implication of Result 1, as suppression costs are assumed to be a monotonically increasing function of suppression effort. Thus, contrary to conventional thought, fuel treatments will not necessarily reduce the suppression costs of nearby fires. Corollary 1.2 reaches a similar conclusion for a fire's size. Intuitively, the negative direct effect of fuel treatments on a fire's size, $\frac{\partial S(E_i,F_i)}{\partial F_i}$, will be enhanced through the indirect effect of increasing suppression effort, $\frac{\partial S(E_i,F_i)}{\partial E_i} \cdot \frac{dE_i}{dF_i}$, under q-complementarity. In contrast, if fuel treatments and suppression effort are q-substitutes, then the direct effect of fuel treatments on a fire's size will be offset by a reduction of suppression effort, leaving the total effect ambiguous. Thus, fuel treatments are not guaranteed to reduce the size of nearby fires and depend critically on the endogenous effort allocation response of fire managers.

The relationship between fuel treatments and suppression effort has important implications for suppression costs and fire size. Determining whether fuel treatments and suppression effort are q-complements or q-substitutes requires an understanding of whether fuel treatments disproportionately enhance some units of effort relative to others. For example, fuel treatments and suppression effort are q-substitutes if fuel treatments disproportionately enhance the effectiveness of hand crews relative to air tankers, and q-complements if fuel treatments disproportionately enhance the effectiveness of air tankers relative to hand crews. Qualitative evidence suggests that fuel treatments enhance the ability of hand crews to conduct direct and indirect attacks, suggesting that fuel treatments may reduce expected fire sizes relatively more for low levels of fire suppression effort allocations (Romero and Menakis, 2013). If so, then fuel treatments become substitutable for fire suppression effort and lead the fire manager to allocate fewer resources to fighting fires that occur close to fuel treatments.

Our results thus far have focused on the "own-fire" effects of fuel treatments—i.e., the effects of fuel treatments on a nearby fire. The binding constraint of effort resources also has implications for the effects of fuel treatments on other fires. Intuitively, if fuel treatments increase the marginal productivity of suppression effort, a fire manager will reallocate effort toward the fire with fuel treatments. If the effort constraint is binding, then this effort is drawn from other fires until marginal benefits minus marginal costs are equal across all fires. The opposite is true if fuel treatments decrease the marginal productivity of suppression effort.

Result 2. Fuel treatments will induce spillovers onto other fires if the suppression effort resource constraint binds. Specifically, fuel treatments will direct suppression effort toward other fires if they are q-substitutes,

$$\frac{dE_j^*}{dF_i} > 0 \iff -\frac{\partial^2 S(E_i, F_i)}{\partial F_i \partial E_i} < 0,$$

and draw suppression effort away from other fires if they are q-complements.

Corollary 2.1. If the effort resource constraint binds, fuel treatments may increase or decrease total fire suppression costs, regardless of whether fuel treatments and suppression effort are q-complements or q-substitutes.

Corollary 2.2. If the effort resource constraint does not bind, fuel treatments will decrease total fire suppression costs if and only if fuel treatments and fire suppression efforts are q-substitutes.

The immediate implication of Result 2 is that our empirical strategy will need to consider a possible violation of the stable unit treatment value assumption (SUTVA). That is, one fire's effect of being close to a fuel treatment will depend on the proximity of all other fires to fuel treatments. We discuss how we address this challenge in Section 4. Corollary 2.1 demonstrates that these spillover effects also have implications for fuel treatments' effect on total fire suppression costs across all fires. To understand how total suppression costs could go up, consider the situation in which there are only two fires and $E_1^* > E_2^*$ since there are more assets at risk for Fire 1. Now, suppose that Fire 2 is close to a fuel treatment and that fuel treatments are q-substitutes to suppression effort, which implies that even more effort is now directed toward Fire 1. Since suppression costs are convex in effort, this implies that total suppression costs would increase. Corollary 2.2 demonstrates that total suppression costs are guaranteed to decrease with fuel treatments in a situation of q-substitutability and a non-binding resource constraint.

3.3 Testable Implications

The results thus far suggest that fuel treatments may not reduce suppression costs or fire size in the presence of endogenous fire suppression effort. Does this imply that fuel treatments are not necessarily economically beneficial? A simple application of the envelope theorem demonstrates that they are, under one condition.

Result 3. Fuel treatments increase the value of a fire manager's economic program provided the direct effect of fuel treatments on fire size is negative: $\frac{\partial S(E_i^*, F_i)}{\partial F_i} < 0$.

Thus, the direct effect of fuel treatments on fire size is a sufficient condition for determining whether fuel treatments have positive economic benefits. Intuitively, while fuel treatments will induce changes in suppression effort allocation, effort will be adjusted to balance the marginal benefits of reduced fire damages with the marginal cost of fire suppression so that the behavioral response will not have a first-order effect.

Unfortunately, even if fuel treatments were randomly assigned, we cannot identify the direct effect of fuel treatments on fire size given the endogenous response of fire suppression effort. How, then, can we know if fuel treatments provide economic benefits? Recall that the total effect of fuel treatments on fire size, which is what we identify empirically, is

$$\frac{dS(E_i^*, F_i)}{dF_i} = \frac{\partial S(E_i^*, F_i)}{\partial E_i} \cdot \frac{dE_i^*}{dF_i} + \frac{\partial S(E_i^*, F_i)}{\partial F_i}.$$

Now, suppose that fuel treatments and suppression effort are q-substitutes, which implies $\frac{dE_i^*}{dF_i} < 0$ (Result 1). Then we have the following:

$$\frac{dS(E_i^*, F_i)}{dF_i} < 0 \iff \frac{\partial S(E_i^*, F_i)}{\partial F_i} < -\frac{\partial S(E_i^*, F_i)}{\partial E_i} \cdot \frac{dE_i^*}{dF_i} < 0 \implies \frac{\partial S(E_i^*, F_i)}{\partial F_i} < 0.$$

That is, a negative effect of fuel treatments on fire size, including the endogenous effort response, implies the direct effect of fuel treatments on fire size is negative, so long as fuel treatments and suppression effort are q-substitutes. From Corollary 1.1, we know that the impact of fuel treatments on suppression costs is a sufficient condition for the q-substitutability of fuel treatments and suppression effort:

$$\frac{dC(E_i^*)}{dF_i} < 0 \iff \frac{dE_i^*}{dF_i} < 0.$$

Thus, rejecting the null hypothesis that $\frac{dS(E_i^*, F_i)}{dF_i} \geq 0$ or $\frac{dC(E_i^*)}{dF_i} \geq 0$ indirectly rejects the null hypothesis of $\frac{\partial S(E_i^*, F_i)}{\partial F_i} \geq 0$, implying that fuel treatments are economically beneficial. We use this result to test for the presence of economic benefits of fuel treatments in our empirical setting.

4 Empirical Framework

We aim to identify the effect of fuel treatments on fire suppression costs and fire size by taking advantage of variations in fire ignition and fuel treatment locations within national forests. Intuitively, this strategy compares the suppression cost and size of fires that start within the same national forest but are exposed to different amounts of fuel treatments within a certain radius of their ignition location (Figure 3a). Such comparisons, however, may be subject to bias as fuel treatments and fire suppression effort are jointly determined via socioeconomic and environmental factors. For example, one of the main goals of implementing fuel treatments is to protect communities most at risk from wildfires. Hence, fuel treatments are typically located closer to homes in the WUI (Schoennagel et al., 2009). At the same time, wildfire suppression effort, and thus costs, are disproportionately higher for fires that threaten homes (Bayham and Yoder, 2020; Baylis and Boomhower, 2023; Plantinga et al., 2022). Additionally, the costs of conducting fuel treatments correlate with topographic (e.g., lower slopes and elevations), vegetation characteristics (e.g., site productivity), and economic (e.g., proximity to roads) variables that also influence fire suppression costs. To address these concerns, we take advantage of exogenous variation in fuel treatment locations arising from spatial variation of late-successional reserves (LSRs) from the Northwest Forest Plan.[13]

4.1 Data

We construct a dataset that combines administrative data of NWFP land use allocations with fuel treatment and wildfire outcomes in the Pacific Northwest from 2006-2023. Our data come from various sources with varying degrees of spatial and temporal coverage. A summary of the main data sources for wildfire costs, fuel treatments, NWFP land use allocations, and the name, source, and description of all control variables used in our analysis are provided in Table S.2 and Table S.3.

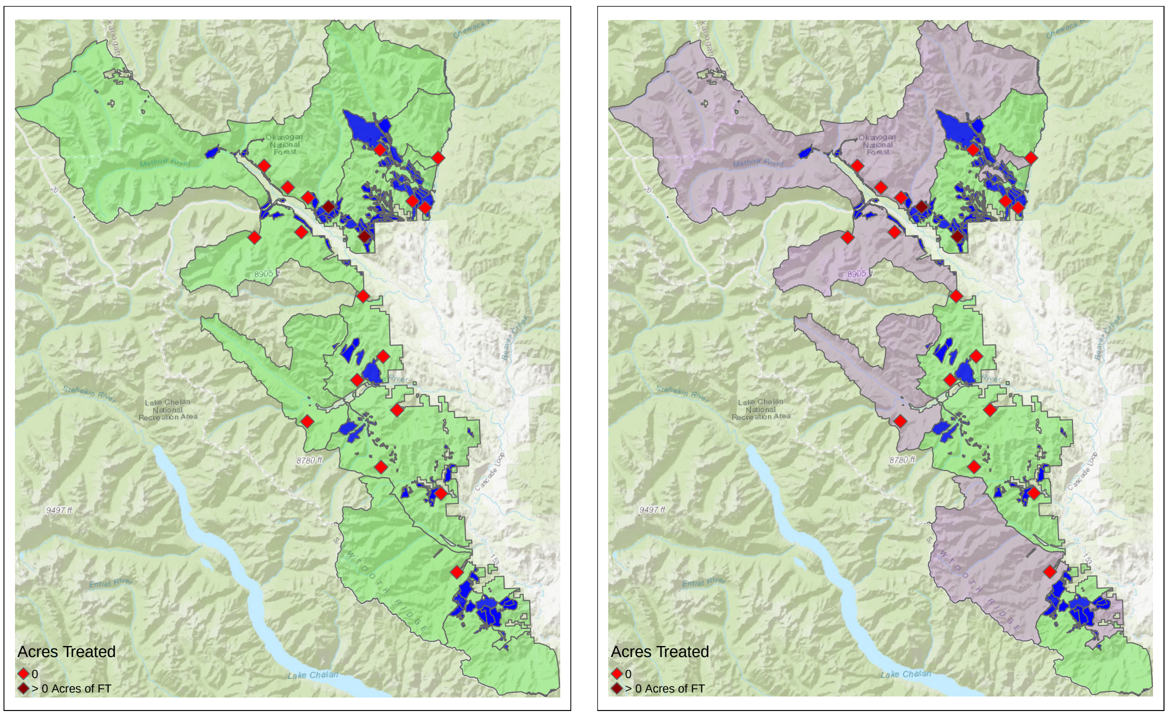
Information on the cost, date, and location of wildfires comes from two sources comprising two different periods. The National Fire and Aviation Management Web Applications (FAMWEB), used in Baylis and Boomhower (2023), comprises wildfires igniting from 2006-2014 (FAMWEB, 2023). Because the FAMWEB collection system ended in 2014 and was replaced by the "Wildland Fire Incident Locations" data provided by the National Interagency Fire Center (NIFC), we use this source for fires post-2014 (NIFC, 2024). For each fire, we obtain environmental and socioeconomic determinants of wildfire behavior and fire suppression effort. Environmental variables include topographic (e.g., elevation, slope, and aspect), vegetation (e.g., fuel type and fuel loads), and historic fire risk (e.g., mean fire return interval) at the ignition point from LANDFIRE, along with weather conditions (e.g., temperature, precipitation, wind speed, and vapor pressure deficit) at the time of ignition from PRISM and GridMET.[14] We also estimate the distance between the

[13] The interested reader can turn to Figure S.1 and Appendix C for a visual representation of the data generating process of fuel treatments and wildfires along with a more detailed discussion of the sources endogeneity driving fuel treatment location and fire suppression costs.

[14] LANDFIRE data can be accessed at `https://landfire.gov/`, PRISM at `https://prism.oregonstate.edu/`

Figure 3: Baseline & IV Identification Strategies Intuition

(a) Baseline (b) IV



The panels above display fire ignition locations (red) and fuel treatments (blue) within the Methow Valley Ranger District during the 2013 fire season. The left panel illustrates the "baseline" estimation strategy, which leverages the proximity of fire ignitions to fuel treatments occurring within the same national forest and season. The right panel depicts the "Instrumental Variable" (IV) approach, highlighting protected areas (LSRs) in purple and unreserved areas (Matrix) in light green.

ignition point of each fire and valuable nearby resources, including distance to nearest Census Block in the WUI, U.S. Forest Service roads, and the total housing value within 10 kilometers of an ignition point (Radeloff et al., 2022; USFS, 2023b).

Fuel treatment data come from the USFS FACTS (Forest Service Activity Tracking System) Hazardous Fuel Treatment Reduction database (USFS, 2024). The USFS has systematically recorded management activities in FACTS since 2005 (Adams and Charnley, 2018). Hence, we restrict our sample to fuel treatment activity post-2005. Fuel treatment activities typically fall into three main categories: mechanical and hand (we refer to this category as "mechanical"; e.g., tree removal, mastication of small trees and shrubs, and hand thinning or pruning followed by piling and burning), prescribed burning (e.g., intentional application of fire), and wildfire use (e.g., unplanned wildfires left to burn). We restrict our attention to the effectiveness of mechanical and prescribed burning fuel treatments since they are the types of treatment impacted by the NWFP reserves.

Spatial data on NWFP LSRs and Matrix areas come from the Regional Ecosystem Office (REO), which has the location of such reserves across the Pacific Northwest (REO, 2013). The REO dataset has the exact location of LSRs, while Matrix areas are lumped in the "Other" category, co-occurring with Riparian Reserves.[15] Lastly, we expand our definition of Matrix to be inclusive of other flexible land-use designations from the NWFP, such as "Adaptive Management Areas," which have similar management protocols as Matrix areas.[16] Throughout the rest of this paper, we refer to Matrix areas as being inclusive of Adaptive Management Areas and Riparian Reserves within Matrix areas from the NWFP.

Since our objective is to identify the impact of fuel treatments close to an ignition point on fire size and suppression costs, it requires the inclusion of small fires. For example, if fuel treatments close to a fire reduce the cost of small fires or reduce the likelihood of a small fire turning into a large fire, then limiting our sample to only large fires will not identify the effects of fuel treatments close to an ignition point. However, because fire suppression costs are not systematically recorded for small fires, our sample includes many "zero-cost" fires, of which the majority are small fires that were successfully suppressed through an initial attack.[17] To address this issue, we impute all zero-cost small fires (< 100 acres) with the median cost of suppressing a small non-zero-cost fire in our sample. The rationale for this is that such fires were most likely low-cost initial attack fires. We then drop all large (> 100 acres) zero-cost fires from our sample because these fires might be a part of a fire complex or may be of a significant cost that is not easy to predict.[18] The results of our analysis are robust to different ways of accounting for zero-cost fires, which we describe in subsection 5.1.

explorer/, and GridMET from https://www.climatologylab.org/gridmet.html

[15] To account for the fact that Riparian Reserves have their own set of restrictions and regulations, we control for whether a fire ignites inside of a Riparian Area (as defined by Existing Vegetation Group Type from LANDFIRE). Consistent with the additional regulatory restrictions in Riparian Areas, we find that fires igniting in such areas receive significantly fewer fuel treatments close to their ignition point than fires that ignite in other vegetation types.

[16] See Appendix E for a list and description of all the land-use categories from the NWFP

[17] A little less than half our sample has zero-cost fires, 3,972 in total. These zero-cost fires account for around 45% of all small fires (< 100 acres).

[18] 51 fires meet this criteria.

Because the spatial distribution of private land ownership is correlated with economic and environmental determinants of fire suppression efforts and fuel treatments, we restrict our sample to only those fires that ignite within National Forests. For example, private forest lands are typically located near communities, along river bottoms, and around valley fringes, while National forests were created primarily from lands left after land grants and homesteading had privatized lower-elevation forests (Johnson et al., 2023). To focus on the impact of NWFP reserves, we further restrict our sample to fires that ignite inside the NWFP boundary. In a less restrictive sample, we also include fires that ignite within any of the 17 National Forests that are apart of the NWFP. This sample is less restrictive since some National Forests only lie partly within the NWFP boundary.

LSRs and Matrix areas from the NWFP only occur within non-wilderness areas of national forests; hence, we also restrict our sample to include only fires that ignite outside of wilderness areas or national parks.[19] Restricting our sample to fires that ignite within non-wilderness portions of national forests is essential because fire behavior and suppression strategies are systematically different in wilderness areas (Gebert et al., 2007).

These filtering steps ensure that our samples represent fires that ignite within either LSRs or Matrix (or "Matrix-Like" for the more inclusive sample) areas, which are more comparable given that they were similar plots of land prior to the NWFP. In total, the two samples include 9,923 and 18,722 fires from 2006-2023. Table 1 provides a summary of our fuel treatment and fire cost data. The major discrepancies between the median and averages in our dataset are consistent with previous literature showing that fire suppression costs are a right-tail-driven process. For example, the average cost of suppressing a fire ($471,708) is approximately three hundred times as large as the median cost of suppressing a fire ($1,568). We see a similar pattern for acres burned as the average is 503 and the median is 0.1. These results are consistent with the fire suppression policies and practices of the Forest Service, where 98% of fires started are successfully suppressed within a day, while the other 2% account for 95% of fire damages and effects (Calkin et al., 2005).[20] In total, $4.68 billion USD was spent on fire suppression in our sample, the majority of which occurred during the second half of the sample period (Figure 2b).[21] Consistent with qualitative reports, the costs of fuel treatment activities are significantly lower than fire suppression costs, with only $270 million spent on all fuel treatment activities in Matrix and LSRs from 2006-2023.[22]

[19] Parks and wilderness areas were lobbied by the timber industry to be located in high alpine areas and were mostly located in areas with no development before designation (Johnson et al., 2023).

[20] See Figure S.2a for plots of the distributions of the natural log of fire size and cost in our sample.

[21] For reference, the USFS spent $27.8 billion USD in fire suppression costs over the same time period ($35 billion across all federal agencies), so our sample represents a significant portion of total fire suppression costs in the U.S.

[22] The $270 million costs should be interpreted as an overestimate of the true cost because the $217 million spent on mechanical treatments in the FACTS data does not include the revenues from thinning, which often fund other fuel treatment activities, and in some cases cover the full cost of other surface fuel treatments (Belavenutti et al., 2021).

Table 1: Fuel Treatments & Wildfires Descriptive Statistics

	Prescribed Fire	Mechanical	Total Treatments	Wildfires
Average Cost	\$7,578	\$8,191	\$14,160	\$471,897
Median Cost	\$1,476.2	\$960.8	\$1,940.7	\$1,568.3
Total Cost	\$56,654,865	\$222,963,214	\$279,618,079	\$4,682,637,293
Average Acres	56.6	26.3	35.2	503.1
Median Acres	18.3	14.4	13	0.1
Total Acres	423,221	271,707	694,927	4,991,788
Total Cost/Acre	\$133.9	\$820.6	\$402.4	\$938.1
No. Obs	7,476	10,348	19,747	9,923
Coverage	2006-2023	2006-2023	2006-2023	2006-2023

The first three columns show size and cost statistics for Prescribed Fires, Mechanical, and Total Fuel Treatments (Prescribed Fire + Mechanical) that occur in Matrix and LSR areas in USFS lands in the NWFP area. Cost data for fuel treatments should be interpreted cautiously because FACTS does not have a systematic way of recording cost data. For example, mechanical treatments do not record revenues from sold timber so some treatments will be recorded with 0 cost while others will not take into account revenues into their cost calculation. The fourth column shows size and cost statistics for wildfires that ignite in Matrix and LSR areas in USFS lands in the NWFP area.

4.2 Baseline Estimation Strategy

Following Baylis and Boomhower (2023), we start with the following fixed-effects specification as our baseline regression model:

$$Y_{ift} = \phi \log(FT_{it}) + X'_{it}\beta + E'_{it}\Lambda + \mu_f + \lambda_t + \epsilon_{ift}, \tag{1}$$

where Y_{ift} is the natural log of the cost (or size) of fire i, that starts in national forest f, in month t. Our parameter of interest is ϕ, which represents the percentage change in suppression costs (or size) from a one-percent increase in the acres of fuel treatments occurring within a certain distance of fire i, FT_{it}.[23]

We specify FT_{it} as the acres of fuel treatment, both mechanical and prescribed fires, occurring within a 100-acre circle surrounding the ignition point of the fire within the last ten years of the fire.[24] Taking the sum of both mechanical and prescribed fire fuel treatments recognizes that fuel treatments incorporating both mechanical and prescribed fire treatments are the most effective at reducing wildfire severity (Wimberly et al., 2009; Prichard and Kennedy, 2014). Figure 4 provides

[23]We model the relationship between fuel treatments and fire size/cost through the natural log to be consistent with the fire ecology literature that shows the fuel treatment effectiveness is non-linear and exhibits diminishing returns to scale (Ott et al., 2023). To account for the fact that many fires have zero acres of fuel treatment close to the fire, we take the $\log(x+1)$ transformation of FT_{it}. Our estimates are robust to linear and inverse hyperbolic sine specifications.

[24]We choose ten years to be the cutoff for counting fuel treatments as previous studies have shown that fuel treatment effectiveness is diminished after 9–14 years (Collins et al., 2009; van Wagtendonk et al., 2012; Lydersen et al., 2014). Because mechanical fuel treatments are often conducted in a series of treatments which is followed up by a prescribed burn (e.g. a commercial thin is typically conducted in tandem with other mechanical treatments such as biomass removal or fuel piling), we avoid double counting such fuel treatments by only counting mechanical treatments associated with a given project area once.

an example of how we calculate fuel treatments for a particular fire.[25] We calculate the acres of fuel treatment "close" to a fire instead of the acres of fuel treatment that intersect with a fire's footprint because larger fires are more likely to intersect with fuel treatments due to their size, thus leading to a spurious positive correlation by construction. Additionally, if fuel treatments are used to construct fire lines where the fire is to be stopped and contained, then a fire is unlikely to intersect with the proximate fuel treatments.[26] Because our treatment variable measures the acres of fuel treatment close to an ignition point, our results do not capture all the potential benefits of fuel treatments on wildfire size or suppression costs. For example, fuel treatments that occur further away from an ignition point may still influence the cost and size of large fires that encounter fuel treatments further away from their ignition point.[27]

We include sets of socio-economic and environmental control variables, X_{it} and E_{it}, that influence a fire's size and its cost of suppression (Table S.3). Examples of environmental variables include topographic (i.e., slope, elevation, or aspect at ignition point), weather (i.e., temperature or vapor pressure deficit), vegetation characteristics (i.e. fuel type), and historic fire risk (i.e. mean fire return interval) near the ignition point, while examples of socio-economic variables are the ignition's distance to the WUI or Forest Service Road.[28] To account for the role of previous wildfires in influencing wildfire behavior, we calculate the previous acres burned within the 100-acre circle surrounding an ignition point in the last 10 years.[29] Our national forest, μ_f, and time-fixed effects, λ_t, address various omitted variable bias concerns. National forest fixed effects control for time-invariant unobserved determinants of firefighting costs that are specific to a national forest. Year-month fixed effects control for unobserved changes in firefighting resources and costs over time that are constant across national forests. Lastly, we cluster standard errors at the national forest level.

The identifying assumption in our baseline regression analysis is that unobserved determinants of fire cost and size, ϵ_{ift}, are independent of FT_{it}, conditional on national-forest fixed effects and our other controls. Because both fuel treatments and fire suppression effort are jointly determined via socio-economic and environmental factors, we may expect estimates of ϕ to still suffer from bias even after the inclusion of our controls because of measurement error and unobserved factors that vary within a national forest, like fire risk. For example, while we control for a fire's proximity to WUI and historic fire risk factors, we do not observe the precise locations of homes or ex-ante

[25] We explore the sensitivity of our estimates to different distances and time since fire in Section 5.1

[26] Perimeters of fires are only systematically recorded for large fires (> 1000 acres), and hence any analysis using intersected areas would require restricting the sample to only large fires.

[27] We demonstrate this point in Appendix B by decomposing the total marginal benefit of fuel treatments on fire size and cost across multiple channels.

[28] We do not control for vegetation characteristics that are influenced by fuel treatments in our sample, such as canopy base height, as this would condition on one of the main mechanisms through which fuel treatments influence our outcomes of interest. To address this we calculate all vegetation characteristics as of 2001, so that they represent pre-treatment vegetation characteristics. See Table S.3 for more details on such variables.

[29] Note that previous burned acres is sometimes considered another form of fuel treatment and have been shown to reduce wildfire severity (Belval et al., 2019). For fires that do not threaten structures and assets at risk the USFS lets such fires burn as "Wildfire Use" (WFU) (van Wagtendonk, 2007).

wildfire risk at the time a fire ignites or a fuel treatment is conducted.[30] Since we would expect both home proximity and ex-ante fire risk to be positively correlated with fire suppression effort and fuel treatments, our baseline estimate of fuel treatments' effect on suppression costs is likely to suffer from an upward bias—i.e., the expected negative effect of fuel treatments on suppression costs will be understated.

A regression of $\log(FT_{it})$ on the observable characteristics of fire suppression effort, X_{it}, and environmental factors that influence wildfire behavior, E_{it}, confirms that fuel treatments highly correlate with such factors (Table 2). Specifically, fires that receive more fuel treatments close to their ignition point are, on average, closer in proximity to the WUI, more housing units, and wealthier neighborhoods. Consistent with our hypothesis that fuel treatments are located in areas of higher fire risk, we find that fuel treatments occur in areas that historically experienced more frequent fire and that are typically drier and warmer in the summer.

4.3 Instrumental Variables Strategy

To overcome endogeneity concerns, we use spatial variation in NWFP reserves (LSRs) within National Forests as an instrument for the extent of fuel treatment activity occurring close to a fire. The intuition behind this estimation strategy is to compare fires that occur within the same national forest during the same time of year but differ in whether the fire ignites within an LSR or a Matrix area (Figure 3b).

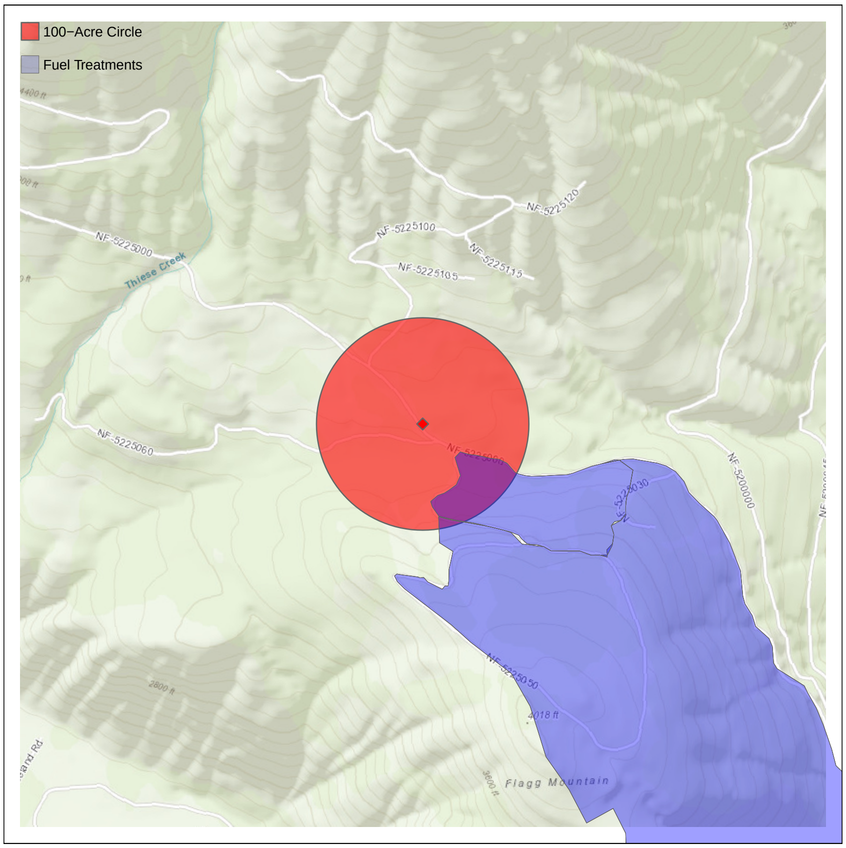
We argue that variation in fuel treatments stemming from LSRs is quasi-random because the NWFP was a compromise between timber production and species conservation, where Matrix lands would have been reserved in a world with more stringent species protection. Additionally, LSRs were chosen based on the northern spotted owl's nesting, roosting, foraging habits, and dispersal ecology (Gaines et al., 2022), which is unlikely to be correlated with determinants of wildfire behavior and fire suppression effort. Because the vast majority of the fires in our sample start in dry forests, there are even smaller distinctions between LSRs and Matrix areas, as many scientists decried the inclusion of reserves in dry forests because of the stark ecological differences in old-growth between dry and wet forests (Spies et al., 2019). Finally, because LSRs have had the unintended consequence of restricting fuel treatment activity within such areas, we hypothesize that fires igniting within such areas are less likely to be in close proximity to fuel treatments.

More formally, our instrument is a binary variable equal to one if a fire ignites inside an LSR and zero otherwise.[31] Denoting our instrument as LSR_i, the first-stage equation relating fuel treatments

[30] Measures of wildfire risk, such as wildfire hazard potential (Dillon and Gilbertson-Day, 2020), measure risk based on conditions in 2014 or later. As a result, this variable is a function of both our dependent and main independent variables for many of the fires in our sample; hence, it would be improper to control for it. Instead, we control for historic fire risk factors since they are not influenced by wildfires or fuel treatments in our sample.

[31] In alternative specifications, we define the instrument as the number of acres of land within an LSR surrounding the ignition point of a fire to account for the fact that a fire may occur close to the border of Matrix-LSR.

Figure 4: Example Construction of FT_{it} for Flagg Mountain Fire - 2020



The above map visually demonstrates how FT_{it} is calculated for a particular fire, the Flagg Mountain Fire, a 0.1 acre fire that occurred close to Mazama, WA, in 2020. The red star shows the ignition point location, the red circle is the area from which fuel treatments are to be calculated (in this case, 100 acres surrounding the ignition point), and the blue shows the location of fuel treatments close to the fire. Multiple treatments occur within the same blue polygon: a mechanical thin in 2015, a machine pile in 2016, and a pile burn in 2019. The intersected area of the fuel treatments and red circle is 10 acres. Since our fuel treatment variable is defined to be the acres of mechanical treatments (no double counting) plus prescribed fire acres, FT_{it} is equal to 20 acres.

Table 2: Balance Test Regressions - Endogenous Regressor v. Instrument

Economic Variables

	Dist WUI	Dist FS Road	Total Housing Value	Population	No. Housing Units
$\log(FT_{it})$	-0.533***	-0.069***	43.510**	165.720**	95.382***
	(0.086)	(0.013)	(17.889)	(61.460)	(29.789)
LSR_i	0.908*	0.107	-11.046	-86.682	-39.854
	(0.453)	(0.063)	(20.494)	(120.620)	(64.908)
N	9923				

Topography & Weather

	Slope	Elevation	South Slope	Wind Speed	ERC
$\log(FT_{it})$	-0.869***	-40.344***	0.003	-0.022***	0.095
	(0.183)	(7.623)	(0.006)	(0.007)	(0.117)
LSR_i	2.735***	43.985	0.015	-0.009	0.362
	(0.345)	(48.324)	(0.011)	(0.029)	(0.390)
N	9923				

Historic Fire Risk Variables

	MFRI	Precip - CN	Temp Mean - CN	Temp Max - CN	VPD - CN
$\log(FT_{it})$	-0.331*	-0.460***	0.160***	0.266***	0.523***
	(0.162)	(0.132)	(0.025)	(0.028)	(0.060)
LSR_i	-0.170	0.495	-0.211	-0.466	-1.341**
	(0.837)	(0.496)	(0.224)	(0.286)	(0.574)
N	9923				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports the results of 30 separate regressions regressing the natural log of acres of total fuel treatment, $\log(FT_{it})$ and an indicator of whether a fire occurs in a late-successional reserve, LSR_i, on sets of economic and environmental (topography, weather, & historic fire risk) variables with the inclusion of National Forest and year-month of sample fixed effects. The sample includes wildfires in 17 National Forests that are apart of the NWFP from 2006–2023. Economic variables are distance to WUI & USFS road and the total housing value, population, and housing units within 10km of the ignition point. Topographic variables are the slope and elevation at a fires ignition point, a dummy variable equal to 1 if the slope at the ignition point is on a south facing slope aspect, while weather variables are the wind speed and energy release component (ERC) on day of ignition. Historic fire risk control variables include mean fire return interval (MFRI), and the 30-year climate normals in August for precipitation, temperature mean, temperature max, and max vapor pressure deficit (VPD) at the ignition point for a given fire. Standard errors are clustered at the national-forest level.

and fires igniting in an LSR is

$$\log(FT_{it}) = \delta LSR_i + X'_{ift}\Pi + E'_{ift}\Psi + \mu_f + \lambda_t + u_{ift}, \tag{2}$$

and the reduced-form equation relating fire suppression costs and LSR status is

$$Y_{ift} = \eta LSR_i + X'_{ift}\Gamma + E'_{ift}\Omega + \mu_f + \lambda_t + v_{ift}. \tag{3}$$

The ratio of the reduced-form and first-stage coefficients, η/δ, is equivalent to the IV estimand of the percentage change in fire suppression costs (or size) from a one-percent increase in fuel treatments within a certain distance of a fire's ignition.

The identifying assumptions underlying our IV approach are i) relevance: LSR_i has a strong correlation with fuel treatments, ii) exogeneity: LSR_i is (conditionally) uncorrelated with the unobservable determinants of fire suppression costs, and iii) exclusion: LSR status has no direct impact on fire suppression costs. Our instrument would violate the first assumption if LSR status did not substantially hinder the Forest Service's ability to conduct fuel treatments. We test this assumption directly by estimating equation (2) in Section 5. We also examine the plausibility of the exogeneity assumption by regressing LSR_i on the observable determinants of fire suppression costs with the inclusion of National Forest and year-month fixed effects. In general, we find a considerably better balance on observable characteristics when using LSR_i than $\log(FT_{it})$ (Table 2). Lastly, the exclusion restriction would fail if fire suppression efforts were directly responsive to characteristics associated with LSRs—e.g., a concern for saving old-growth forests. Although we cannot directly test this assumption, we hypothesize this not to be the case because the Forest Service's top priorities in fire suppression are human life, then structures, and lastly natural resources (ESA habitat, watersheds, etc.) (USFS, 2000).[32]

5 The Effect of Fuel Treatments on Fire Size and Suppression Costs

Table 3 presents the first-stage (2), reduced-form (3), IV, and baseline (1) regression results for both the natural log of fire suppression costs and size using an indicator variable equal to one if a fire ignites inside of a LSR as an instrument for $\log(FT_{it})$. The estimated first-stage relationship implies that fires igniting inside of LSRs receive 13.7% fewer acres of fuel treatments within a 100-acre radius of their ignition point than fires igniting inside of Matrix areas, on average. This first-stage relationship is statistically different from zero, with an F-statistic equal to 42.5, suggesting that LSR status is a strong instrument for fuel treatments. The estimated reduced-form relationships demonstrate that fires igniting inside of LSRs are 7.4% larger (p-value of 0.1961) and 12.2% more expensive (p-value of 0.0148), on average. The IV estimates show that a one-percent increase in fuel treatments within a 100-acre radius of a fire's ignition reduces fire suppression costs by 0.89

[32]Correspondingly, Plantinga et al. (2022) find no evidence of increased fire suppression effort in ESA or sensitive watershed habitats.

percent (p-value of 0.0356) and fire size by 0.61 percent (p-value of 0.1997), on average. The IV estimates are considerably larger in magnitude than their corresponding baseline fixed-effects OLS estimates, as expected, but less precisely estimated.

The IV estimates imply that fuel treatments and fire suppression effort are q-substitutes—that is, fire managers allocate less suppression effort toward fires that are in close proximity to fuel treatments. While this has the effect of decreasing the suppression costs of such fires, it also has the effect of offsetting any direct reductions that fuel treatments have on fire size. Thus, fuel treatments are not guaranteed to reduce a fire's size in such situations, although we find weak evidence that they do in our context.

Following from our conceptual model, a negative direct effect of fuel treatments on fire size is a sufficient statistic for the economic benefits of fuel treatments. Since we cannot empirically identify the direct effect of fuel treatments on fire size, we test for its existence indirectly by testing the null hypothesis that the effects of fuel treatments on fire size or cost are weakly positive. We find evidence to reject the null hypothesis (p-value of 0.0014) using an intersection-union hypothesis test (Casella and Berger, 2002).[33] Rejecting the null implies that the effects of fuel treatments on fire size and cost are strictly negative, suggesting that fuel treatments are generally economically beneficial.

5.1 Robustness Checks

We conduct a variety of robustness checks to evaluate the sensitivity of results to alternative variable definitions, specifications, and samples. To address concerns that Matrix and LSRs areas may be systematically different across observable determinants of fire suppression efforts, we conduct a matching procedure in which each fire in our sample is matched exactly to a fire that occurs in the same vegetation type, National Forest, and during the same month. Fires are then inexactly matched to find the optimal covariate balance across the most important determinants of fire suppression costs and size (distance to WUI and USFS roads, elevation, slope, vapor pressure deficit, and wind speed) through the use of a genetic search algorithm, resulting in 3274 matches and 6548 fires in total. The matched IV estimation results are slightly smaller in magnitude than our unmatched IV regression results but are more precisely estimated and both statistically significant at the 5% level (Table S.4).

Our conceptual model (section 3) raised the concern that we may see violations of SUTVA due to suppression effort spillovers when resources for fire suppression are scarce. Namely, effort may be disproportionately allocated away from fires with fuel treatments to those with no fuel treatments if effort and fuel treatments are q-substitutes, leading to an overestimate (underestimate) of the magnitude of fuel treatments' effect on fire suppression costs (fire size). We explore this possibility by re-estimating our IV regression with added controls for scarcity in fire suppression resources

[33] See Appendix D for more details on how we conduct this hypothesis test.

Table 3: IV First Stage & Reduced Form Regression Results

	First Stage	**Reduced Form**		**IV**		**OLS**	
	$\log(FT_{it})$	**Size**	**Cost**	**Size**	**Cost**	**Size**	**Cost**
LSR_i	-0.137***	0.074	0.122**				
	(0.021)	(0.055)	(0.045)				
$\log(FT_{it})$				-0.540	-0.893**	-0.035*	-0.016
				(0.405)	(0.391)	(0.018)	(0.018)
1st Stage F-Stat	42.5						
R^2	0.19	0.13	0.13	0.07	-0.10	0.13	0.13
N	9923	9923	9923	9923	9923	9923	9923

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports the results of seven separate regressions for the first stage, reduced form, full IV estimates, and OLS estimates using an indicator for whether a fire occurs within a late-successional reserve, LSR_i, as an instrument for the natural log of fuel treatments $\log(FT_{it})$. The sample includes wildfires inside of Matrix & LSR areas in the NWFP area from 2006–2023. The first column reports the coefficient estimates for the first stage, $\log(FT_{it})$, while the second and third columns are the reduced form results on the natural log of fire size and suppression costs. The fourth and fifth columns are the full 2SLS regression results on the natural log of wildfire size and suppression cost. The sixth and seventh columns are the baseline OLS estimates on the natural log of wildfire size and suppression cost. Each regression includes economic and environmental control variables. Economic controls include a cubic for distance to WUI Census Block & USFS road along with the total population, housing units and housing value within 10km of the ignition point. Environmental controls include vegetation characteristics: previous acres burned in the last ten years within the 100-acre ignition cirlce, an indicator if in a Riparian area, fuel model type, canopy height, canopy bulk density, and canopy base height, topographic characteristics: slope, elevation, aspect class, and topographic ruggedness (TRI) at the ignition point, weather controls: mean and max temperature, wind speed, precipitation, energy release component (ERC), and vapor pressure deficit (VPD) on day of ignition, and historic fire risk controls: mean fire return interval (MFRI) and the 30-year climate normals in August for precipitation, temperature mean, temperature max, and max vapor pressure deficit (VPD). National forest fixed effects include the 17 national forests apart of the NWFP. Standard errors are clustered at the national-forest level. First stage F-statistics are calculated via cluster robust-standard errors from the Fixest package in R (Laurent, 2018).

and the number of concurrent fires that are within close proximity to fuel treatments ($FT_{it} > 0$).[34] Following Gebert et al. (2007), we control for the scarcity of fire suppression resources by calculating the difference in the average number of fires occurring in a state from 2000-2020 to the realized number of co-occurring fires in the state where a fire ignites.[35] The main IV results do not change meaningfully with the inclusion of these controls (Table S.5), suggesting that fuel treatments may not have meaningful spillover effects on other fires. This is corroborated by the insignificant effect of the number of concurrent fires close to fuel treatments. In contrast, the positive and significant effect of the number of concurrent fires suggests that scarce resources may influence the size and costs of suppressing fires; however, the effect is relatively small—e.g., one additional concurrent fire (above average) increases a fire's size by 0.1%—and may be picking up variation in general fire conditions that are not controlled for by our other control variables. Overall, there is not

[34] Implicitly, we are assuming that fires are exchangeable—i.e., potential fire size and cost only depend on the number of treated fires—and linear in their spillover effects on other fires (Vazquez-Bare, 2023).

[35] Our sample of fires does not have information on when a fire is contained; thus, we supplement our data with a wildfire ignition dataset from the USFS that has containment information (Short, 2023). Unfortunately, this dataset only consists of fires up to 2020; hence, the sample estimated in Table S.5 is smaller (8407 fires) than our main sample of 9923 fires.

much evidence suggesting scarce firefighting resources plays a meaningful role in the allocation of suppression effort across fires.

Another concern with our approach is that our estimates may be sensitive to changes in the specified distance for which we calculate fuel treatments close to an ignition point. We explore this possibility by re-estimating our IV regression for fire suppression cost using different specifications of the fuel treatment circle size: 50, 75, 100, 125, and 150 acres. We find that the magnitude of the IV estimate is larger for smaller treatment circles but less precisely estimated as there are fewer treated fires (Figure S.3). Increasing the treatment circle improves precision but attenuates the estimate towards zero, as fuel treatments that are further away from a fire's ignition point are less likely to influence fire size and suppression costs. Nevertheless, our IV estimates for suppression costs are statistically significant at the 5% level across all specifications.

We also explore the sensitivity of our IV estimates to changes in our estimation sample. Table S.6 shows the IV estimation results when estimating on 4 different samples of fires: i) lightning fires only, ii) fires occurring in the 17 National Forests apart of the NWFP, iii) fires that are within 2km of a Matrix-LSR border, and iv) fires that are not associated with a complex (2015-2023).[36] The lightning-only sample addresses concern that the probability of a human ignition may be correlated with a fire's LSR or Matrix status. Including fires that occur in any part of the 17 national forests in the NWFP explores how the results generalize across a larger area of interest. Restricting the sample to fires that occur close to Matrix-LSR boundaries addresses concerns that Matrix and LSR areas are systematically different by focusing on areas in which they are most likely to be similar. Lastly, limiting our sample to non-complex fires addresses concerns that fire sizes and costs may not be accurately recorded for fires that are part of a complex. In general, we find that the signs and magnitudes of coefficients are not altered much by the change in samples.

We explore how our IV estimates are sensitive to different specifications of our endogenous regressor and instrument. Table S.8 shows how the results of our IV estimate change when using: i) a linear specification on FT_{it}, ii) taking the inverse hyperbolic sine transformation of FT_{it}, iii) calculating fuel treatments that occur within the last 5 years instead of 10, and iv) using a continuous measure of LSR as an instrument for $\log(FT_{it})$.[37] We find that our IV estimates for suppression costs are statistically significant at the 5% level across all specifications (with the exception of our linear specification which is significant at the 10% level).

We also explore how our IV estimates are sensitive to different specifications of our dependent variable of interest. Table S.8 shows how the results of our IV estimate change when: i) dropping fires that have an originally reported zero cost, ii) indicators for above median fire size or cost iii) average burn severity.[38] The first two robustness checks address concerns with our choice of

[36] A complex is a fire in which multiple fires (with different ignition locations) merge into a single fire. Costs for such fires are recorded separately for each wildfire ignition point so we can have multiple fires in our sample associated with a single complex.

[37] This continuous measure is analogous to FT_{it}, in that it is the number of acres inside of a 100-acre circle around the fires ignition point that are under a LSR designation status.

[38] This continuous measure is analogous to FT_{it}, in that it is average burn severity within the 100-acre circle around the fires ignition point. Burn severity is calculated based on the year of fire from MTBS.

including small (< 100 acre) zero-cost fires and replacing them with the median cost of suppressing small fires in our sample. When estimating i), the signs and magnitudes of our estimates are unchanged; however, our IV estimate is no longer statistically significant, which we argue is due to the fewer observations and, consequently, counterfactual comparisons across small fires that occur in the same national forest and time of year. Consistent with our main IV results, we find that fuel treatments significantly reduce the probability of a fire's cost being above the median, with no significant effect on fire size. When estimating iii), we find that fuel treatments do, in fact, reduce burn severity, consistent with the fire ecology literature (Kalies and Yocom Kent, 2016; Wimberly et al., 2009; Safford et al., 2012).

Lastly, we check the robustness of our IV estimates to the inclusion of different sets of fixed effects. Table S.9 shows how the IV estimation results change when: i) replacing national forest for ranger district fixed effects, ii) replacing year-month fixed effects for year and month (of year) fixed effects, iii) replacing year-month fixed effects for state-year and state-month (of year) fixed effects, and iv) replacing year-month fixed effects for state-year-month fixed effects. Ranger districts are smaller units than National Forests and are more directly involved in land management implementation, and thus, such fixed effects can capture time-invariant unobserved heterogeneity that occurs across the ranger district level. Including time-by-state fixed effects addresses concerns that different states within the NWFP may be following different trends in fire sizes or suppression costs over time. In general, we find that our estimates do not meaningfully change with the inclusion of these various fixed effects.

5.2 Counterfactual Costs & Benefits of Fuel Treatments

To illustrate the economic significance of fuel treatments on fire size and suppression costs, we estimate the counterfactual benefits that would have arisen from a landscape-wide expansion of fuel treatments during our sample period, relative to the associated costs. Our empirical strategy does not focus on quantifying damages from wildfires, such as smoke and property loss. Therefore, our main measure of economic benefits is the reduction in fire suppression costs, which account for less than 1% of the total estimated annual economic cost of wildfires (JEC, 2023). This approach contrasts with our test of the direct effect of fuel treatments on fire size, which assesses whether any economic benefits stem from fuel treatments in general.

We first consider a crude and conservative back-of-the-envelope calculation that likely represents a lower bound for the true cost-effectiveness of fuel treatments. This is due to three factors: i) we measure only reductions in suppression costs, ii) our fuel treatment cost data do not include revenues from mechanical removal fuel treatments[39] and iii) fuel treatments likely reduce suppression costs

[39] Note that we do not model other potential costs from prescribed burns, such as smoke emissions, as this would require analyzing trade-offs in smoke emissions with and without fuel treatments. However, prescribed burns are typically localized and planned to allow communities to prepare for protective measures. Therefore, we believe the benefits in smoke exposure from fuel treatments outweigh their costs. In fact, simulation studies indicate that increasing prescribed burns in the Pacific Northwest and Northern California would significantly reduce population exposure to particulate matter (Kelp et al., 2023).

through other channels (i.e., treatments further away from an ignition point may also influence the cost and behavior of large wildfires).[40]

Suppose that all fuel treatments during our sample period increased proportionately by one percent. We assume this leads to a corresponding one-percent increase in fuel treatment costs, resulting in an increased fuel treatment cost of $2.79 million (Table 1).[41] Given a proportionate one-percent increase in fuel treatments, we then calculate the percent increase in 100-acre fuel treatment intersections for each fire (see Figure S.4 for a demonstration). For each fire, we calculate the counterfactual suppression cost savings by multiplying the percent increase in fuel treatment intersections by our estimated elasticity of fire suppression costs, -0.893 (Table 3), and by the cost of suppressing the fire. Summing the counterfactual savings across all of the fires in our sample provides an estimate of the total benefits from fuel treatments. We find that a one-percent uniform expansion of fuel treatments across the landscape would have resulted in suppression-cost savings of around $8 million and 4,229 fewer acres burned, corresponding to a benefit-cost ratio of $2.88 USD.

We further explore whether fuel treatments yield increasing, constant, or decreasing economic returns to scale by increasing fuel treatments proportionately by five and ten percent. Our analysis reveals that the cost-benefit ratio increases to 4.91 and 5.32, respectively, suggesting increasing returns to scale at current levels of fuel treatment activity. We hypothesize that as fuel treatments increase in size, the frequency of intersections with fire areas also rises, thereby enhancing the likelihood of influencing fire behavior across the landscape.

Our finding that fuel treatments yield increasing economic returns to scale, even under conservative benefit estimates, indicates that current treatment levels fall short of the social optimum. This strengthens the case for recent efforts by federal and state agencies to expand both the scope and intensity of fuel treatment programs on public lands. For example, California and the U.S. Forest Service have set ambitious targets, committing to treat one million acres annually by 2025—a significant shift from the status quo (USFS and State of California, 2020). Our results suggest that such initiatives are likely to generate substantial long-term economic benefits.

6 Discussion

The costs and damages of wildfires have increased considerably in recent decades and are expected to rise across the globe with climate change (Bayham et al., 2022; Abatzoglou and Williams, 2016).

[40]If fuel treatments do indeed influence the behavior and costs of larger fires, this has implications for many fires outside of our sample. For example, some of the most costly fires start on private lands but spill over onto public lands (Levine et al., 2022). It is likely that fuel treatments will also reduce the costs of fighting such fires, which our counterfactual analysis does not account for.

[41]Note that although we are counting the labor costs of fuel treatments as part of our cost measure, many initatives have cited job creation in rural communities as another benefit to increasing the pace and scale of fuel treatments (State of California, 2021). This is especially prescient in the Northwest where 30,000 timber jobs were lost from the NWFP (Ferris and Frank, 2021).

Table 4: Counterfactual Benefits of Increasing Fuel Treatments

	Cost of Treatment	Suppression Savings	Benefit-Cost Ratio	Reduction Acres Burned
1% Increase	$2,796,181	$8,043,549	$2.88	4,229
5% Increase	$13,980,904	$68,700,649	$4.91	36,568
10% Increase	$27,961,808	$148,864,169	$5.32	78,518

The following table shows the cost, benefits, and benefit-cost ratio of what the benefits would have been under different counterfactual scenarios of increasing fuel treatment activity. In the first row fuel treatments are increased proportionately by one percent and we assume that costs increase accordingly by one percent of the total cost of conducting fuel treatment from 2006-2023. In rows two and three fuel treatments and costs are increased by five and ten percent accordingly.

Increasing the pace and scale of fuel treatment activity has been proposed as one solution, with states like California committing to an annual one-million-acre goal of treatment by 2025 (USFS and State of California, 2020). Despite the push for an increase in fuel treatment activity, there has been to this point little empirical evidence to suggest that fuel treatments are a cost-effective means of reducing the impacts of wildfires.

Our study addresses this issue by estimating fuel treatments' impact on two of the major drivers of wildfire costs: fire suppression costs and fire sizes. Using exogenous variation in the location of fuel treatments arising from spatial variation in protected areas, called late-successional reserves, from the Northwest Forest Plan (NWFP), we find that fuel treatments close to a fire's ignition point significantly reduce the cost of suppressing wildfires. Our conservative back-of-the-envelope estimates suggest that for every dollar spent on fuel treatments, three are saved in fire suppression costs. Our results also suggest that fuel treatments exhibit increasing economic returns to scale, as this benefit-cost ratio increases from approximately 3:1 to 5:1 when proportionate spatial expansions of fuel treatments increase from 1% to 10%, respectively.

We also demonstrate the challenges of identifying the effectiveness of fuel treatments caused by the mediating response of fire suppression effort allocation across fires. Our results suggest that fuel treatments and fire suppression effort are q-substitutes, implying that suppression effort is shifted away from fires that ignite close to fuel treatments. While this has the effect of reducing suppression costs for fires near fuel treatments, it also attenuates the effectiveness of fuel treatments in reducing the size of nearby fires. Further, q-substitutability implies suppression effort can be reallocated to fight other wildfires, although we find little empirical support that fuel treatments have spillover effects on other fires. Nevertheless, we find evidence that fuel treatments directly reduce fire size (i.e., without an endogenous suppression effort response), which is a sufficient statistic for generating positive economic benefits.

Our results indicate that fuel treatments are an effective means of addressing wildfire costs, despite identifying only one dimension through which fuel treatments can influence fire size and suppression costs. In particular, we do not identify the potential role that fuel treatments play in influencing fire ignitions, nor do we account for the impact that fuel treatments may have in mitigating the spread of large fires away from their ignition point (Appendix B). Further, our results do not capture how fuel treatments' impact on fire size and severity influences other significant contributors to the costs of wildfires, such as health effects, property damage, and labor market impacts (Bayham et al., 2022; Borgschulte et al., 2022; Heft-Neal et al., 2023). Thus, our estimates of the economic benefits of fuel treatments are likely conservative and could be significantly larger once all potential sources are accounted for.

Finally, because our findings suggest the potential for economic benefits from increasing fuel treatment activities, our study underscores the need to align environmental policies with climate adaptation goals. We show that reserves under the NWFP, established in response to the Endangered Species Act, have unintentionally reduced fuel treatments in these areas, thereby increasing wildfire risk for the very species these policies aim to protect, while also increasing the public costs of wildfire suppression. These reserves are one of several environmental policies—including the Clean Air Act, Wilderness Areas, and NEPA—that limit agencies' capacity to conduct fuel treatments on public lands. We suggest the public take a closer look at how such policies have unintentionally prevented active management of forests on public lands and explore appropriate reforms that encourage active management.

References

Abatzoglou, John T. and A. Park Williams, "Impact of Anthropogenic Climate Change on Wildfire across Western US Forests," *Proceedings of the National Academy of Sciences*, October 2016, *113* (42), 11770–11775. doi: 10.1073/pnas.1607171113.

Adams, Mark D.O. and Susan Charnley, "Environmental Justice and U.S. Forest Service Hazardous Fuels Reduction: A Spatial Method for Impact Assessment of Federal Resource Management Actions," *Applied Geography*, January 2018, *90*, 257–271.

Agee, James K. and Carl N. Skinner, "Basic Principles of Forest Fuel Reduction Treatments," *Relative Risk Assessments for Decision –Making Related To Uncharacteristic Wildfire*, June 2005, *211* (1), 83–96.

Anderson, Sarah E., Andrew J. Plantinga, and Matthew Wibbenmeyer, "Inequality in Agency Response: Evidence from Salient Wildfire Events," *The Journal of Politics*, April 2023, *85* (2), 625–639.

Auffhammer, Maximilian, "Climate Adaptive Response Estimation: Short and Long Run Impacts of Climate Change on Residential Electricity and Natural Gas Consumption," *Journal of Environmental Economics and Management*, July 2022, *114*, 102669.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro, "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century," *Journal of Political Economy*, February 2016, *124* (1), 105–159. doi: 10.1086/684582.

Barros, Ana M. G., Michelle A. Day, Thomas A. Spies, and Alan A. Ager, "Effects of Ownership Patterns on Cross-Boundary Wildfires," *Scientific Reports*, September 2021, *11* (1).

Bayham, Jude and Jonathan Yoder, "Resource Allocation under Fire," *Land Economics*, February 2020, *96* (1), 92.

_ , Jonathan K. Yoder, Patricia A. Champ, and David E. Calkin, "The Economics of Wildfire in the United States," *Annual Review of Resource Economics*, October 2022, *14* (1), 379–401.

Baylis, Patrick and Judson Boomhower, "The Economic Incidence of Wildfire Suppression in the United States," *American Economic Journal: Applied Economics*, 2023, *15* (1), 442–73.

Baylis, Patrick W. and Judson Boomhower, "Mandated vs. Voluntary Adaptation to Natural Disasters: The Case of U.S. Wildfires," *National Bureau of Economic Research Working Paper Series*, 2021, *No. 29621.*

Belavenutti, Pedro, Woodam Chung, and Alan A. Ager, "The Economic Reality of the Forest and Fuel Management Deficit on a Fire Prone Western US National Forest," *Journal of Environmental Management*, September 2021, *293*, 112825.

Belval, Erin J., Christopher D. O'Connor, Matthew P. Thompson, and Michael S. Hand, "The Role of Previous Fires in the Management and Expenditures of Subsequent Large Wildfires," *Fire*, 2019, *2* (4).

Boerner, Ralph E. J., Jianjun Huang, and Stephen C. Hart, "Impacts of Fire and Fire Surrogate Treatments on Forest Soil Properties: A Meta-Analytical Approach," *Ecological Applications*, March 2009, *19* (2), 338–358.

Boomhower, Judson, Meredith Fowlie, Jacob Gellman, and Andrew Plantinga, "How Are Insurance Markets Adapting to Climate Change? Risk Selection and Regulation in the Market for Homeowners Insurance," June 2024.

Borgschulte, Mark, David Molitor, and Eric Yongchen Zou, "Air Pollution and the Labor Market: Evidence from Wildfire Smoke," *The Review of Economics and Statistics*, September 2022, pp. 1–46.

Boustan, Leah Platt, Matthew E. Kahn, and Paul W. Rhode, "Moving to Higher Ground: Migration Response to Natural Disasters in the Early Twentieth Century," *American Economic Review*, 2012, *102* (3), 238–44.

Burke, Marshall and Kyle Emerick, "Adaptation to Climate Change: Evidence from US Agriculture," *American Economic Journal: Economic Policy*, 2016, *8* (3), 106–40.

Busby, Gwenlyn, Gregory S. Amacher, and Robert G. Haight, "The Social Costs of Homeowner Decisions in Fire-Prone Communities: Information, Insurance, and Amenities," *Land Use*, August 2013, *92*, 104–113.

Calkin, David E., Jack D. Cohen, Mark A. Finney, and Matthew P. Thompson, "How Risk Management Can Prevent Future Wildfire Disasters in the Wildland-Urban Interface," *Proceedings of the National Academy of Sciences*, January 2014, *111* (2), 746–751. doi: 10.1073/pnas.1315088111.

_ , Krista M. Gebert, J. Greg Jones, and Ronald P. Neilson, "Forest Service Large Fire Area Burned and Suppression Expenditure Trends, 1970–2002," *Journal of Forestry*, June 2005, *103* (4), 179–183.

Cameron, A C and P K Trivedi, *Microeconometrics: Methods and Applications*, Cambridge: Cambridge University Press, 2005.

Casella, George and Roger Berger, *Statistical inference*, 2nd ed., Pacific Grove, CA: Thomson Learning, 2002.

Collins, Brandon M., Jay D. Miller, Andrea E. Thode, Maggi Kelly, Jan W. van Wagtendonk, and Scott L. Stephens, "Interactions Among Wildland Fires in a Long-Established Sierra Nevada Natural Fire Area," *Ecosystems*, February 2009, *12* (1), 114–128.

Converse, Sarah J., Gary C. White, Kerry L. Farris, and Steve Zack, "SMALL MAMMALS AND FOREST FUEL REDUCTION: NATIONAL-SCALE RESPONSES TO FIRE AND FIRE SURROGATES," *Ecological Applications*, October 2006, *16* (5), 1717–1729.

Davis, Raymond J., Bruce Hollen, Jeremy Hobson, Julia E. Gower, and David Keenum, "Northwest Forest Plan—the First 20 Years (1994-2013): Status and Trends of Northern Spotted Owl Habitats," Technical Report, U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station 2016.

_, Janet L. Ohmann, Robert E. Kennedy, Warren B. Cohen, Matthew J. Gregory, Zhiqiang Yang, Heather M. Roberts, Andrew N. Gray, and Thomas A. Spies, "Northwest Forest Plan–the First 20 Years (1994-2013): Status and Trends of Late-Successional and Old-Growth Forests," Technical Report, U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station 2015.

Deschênes, Olivier and Michael Greenstone, "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather," *American Economic Review*, 2007, *97* (1), 354–385.

Dietrich, William, *The Final Forest: Big Trees, Forks, and the Pacific Northwest*, 2010 ed. / with a new preface and afterword ed., Seattle: University of Washington Press, 2010. "Originally published in 1992 by Simon & Schuster." Includes index.

Dillon, Gregory K. and Julie W. Gilbertson-Day, "Wildfire Hazard Potential for the United States (270-m), Version 2020 (3rd Edition)," 2020. https://www.fs.usda.gov/rds/archive/Catalog/RDS-2015-0047-3.

Donovan, Geoffrey H. and Douglas B. Rideout, "A Reformulation of the Cost Plus Net Value Change (C+NVC) Model of Wildfire Economics," *Forest Science*, April 2003, *49* (2), 318–323.

Edwards, Eric and Sara Sutherland, "Does Environmental Review Worsen the Wildfire Crisis?," Technical Report, Property Environment Research Center (PERC) 2022.

Egan, Timothy, *The Big Burn: Teddy Roosevelt and the Fire That Saved America*, Boston, Mass., Godalming: Houghton Mifflin Harcourt ; Melia [distributor], 2011.

FAMWEB, National Fire And Aviation Management Web Applications, "Fire and Weather Data," 2023. https://www.wildfire.gov/application/fire-and-weather-data [Accessed: April 17, 2023].

Ferris, Ann E. and Eyal G. Frank, "Labor Market Impacts of Land Protection: The Northern Spotted Owl," *Journal of Environmental Economics and Management*, September 2021, *109*, 102480.

Finkral, A.J. and A.M. Evans, "The Effects of a Thinning Treatment on Carbon Stocks in a Northern Arizona Ponderosa Pine Forest," *Large-scale experimentation and oak regeneration*, April 2008, *255* (7), 2743–2750.

Gaines, William L., Paul F. Hessburg, Gregory H. Aplet, Paul Henson, Susan J. Prichard, Derek J. Churchill, Gavin M. Jones, Daniel J. Isaak, and Carly Vynne, "Climate Change and Forest Management on Federal Lands in the Pacific Northwest, USA: Managing for Dynamic Landscapes," *Forest Ecology and Management*, January 2022, *504*, 119794.

_ , Richy J. Harrod, James Dickinson, Andrea L. Lyons, and Karl Halupka, "Integration of Northern Spotted Owl Habitat and Fuels Treatments in the Eastern Cascades, Washington, USA," *Forest Ecology and Management*, November 2010, *260* (11), 2045–2052.

Gebert, Krista M., David E. Calkin, and Jonathan Yoder, "Estimating Suppression Expenditures for Individual Large Wildland Fires," *Western Journal of Applied Forestry*, July 2007, *22* (3), 188–196.

Gerlagh, Reyer and B.C.C. van der Zwaan, "Long-Term Substitutability between Environmental and Man-Made Goods," *Journal of Environmental Economics and Management*, September 2002, *44* (2), 329–345.

Hartsough, Bruce R., Scott Abrams, R. James Barbour, Erik S. Drews, James D. McIver, Jason J. Moghaddas, Dylan W. Schwilk, and Scott L. Stephens, "The Economics of Alternative Fuel Reduction Treatments in Western United States Dry Forests: Financial and Policy Implications from the National Fire and Fire Surrogate Study," *Wildfire mitigation*, August 2008, *10* (6), 344–354.

Hashida, Yukiko and David J. Lewis, "The Intersection between Climate Adaptation, Mitigation, and Natural Resources: An Empirical Analysis of Forest Management," *Journal of the Association of Environmental and Resource Economists*, September 2019, *6* (5), 893–926. doi: 10.1086/704517.

Heft-Neal, Sam, Carlos F. Gould, Marissa L. Childs, Mathew V. Kiang, Kari C. Nadeau, Mark Duggan, Eran Bendavid, and Marshall Burke, "Emergency Department Visits Respond Nonlinearly to Wildfire Smoke," *Proceedings of the National Academy of Sciences*, September 2023, *120* (39), e2302409120. doi: 10.1073/pnas.2302409120.

Hessburg, Paul F., Susan J. Prichard, R. Keala Hagmann, Nicholas A. Povak, and Frank K. Lake, "Wildfire and Climate Change Adaptation of Western North American Forests:

A Case for Intentional Management," *Ecological Applications*, December 2021, *31* (8), e02432. https://doi.org/10.1002/eap.2432.

Hicks, JOHN, "ELASTICITY OF SUBSTITUTION AGAIN: SUBSTITUTES AND COMPLEMENTS," *Oxford Economic Papers*, November 1970, *22* (3), 289–296.

Hjerpe, Evan E., Melanie M. Colavito, Amy E.M. Waltz, and Andrew Sánchez Meador, "Return on Investments in Restoration and Fuel Treatments in Frequent-Fire Forests of the American West: A Meta-Analysis," *Ecological Economics*, September 2024, *223*, 108244.

Hoover, Katie and Bruce R. Lindsay, "Wildfire Suppression Spending: Background, Issues, and Legislation in the 115th Congress.," Technical Report, Congressional Research Service 2017.

Hunter, Molly E. and Michael H. Taylor, "The Economic Value of Fuel Treatments: A Review of the Recent Literature for Fuel Treatment Planning," *Forests*, 2022, *13* (12).

JEC, Joint Economic Committee Democrats, "Climate-Exacerbated Wildfires Cost the U.S. between $394 to $893 Billion Each Year in Economic Costs and Damages," Technical Report, Joint Economic Committee Democrats 2023.

Johnson, K. Norman, Jerry F. Franklin, Gordon H. Reeves, Debora L. Johnson, and Susan Jane M. Brown, *The Making of the Northwest Forest Plan: The Wild Science of Saving Old Growth Ecosystems*, Corvallis, Oregon: Oregon State University Press, 2023.

Kalies, Elizabeth L. and Larissa L. Yocom Kent, "Tamm Review: Are Fuel Treatments Effective at Achieving Ecological and Social Objectives? A Systematic Review," *Forest Ecology and Management*, September 2016, *375*, 84–95.

Kelp, Makoto M., Matthew C. Carroll, Tianjia Liu, Robert M. Yantosca, Heath E. Hockenberry, and Loretta J. Mickley, "Prescribed Burns as a Tool to Mitigate Future Wildfire Smoke Exposure: Lessons for States and Rural Environmental Justice Communities," *Earth's Future*, June 2023, *11* (6), e2022EF003468.

Kent, Larissa L. Yocom, Kristen L. Shive, Barbara A. Strom, Carolyn H. Sieg, Molly E. Hunter, Camille S. Stevens-Rumann, and Peter Z. Fulé, "Interactions of Fuel Treatments, Wildfire Severity, and Carbon Dynamics in Dry Conifer Forests," *Forest Ecology and Management*, August 2015, *349*, 66–72.

Kline, Jeffrey D., "Issues in Evaluating the Costs and Benefits of Fuel Treatments to Reduce Wildfire in the Nation's Forests.," Technical Report, U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station 2004.

Kolden, Crystal A., "We're Not Doing Enough Prescribed Fire in the Western United States to Mitigate Wildfire Risk," *Fire*, 2019, *2* (2).

Kousky, Carolyn, "The Role of Natural Disaster Insurance in Recovery and Risk Reduction," *Annual Review of Resource Economics*, 2019, *11* (Volume 11, 2019), 399–418.

_ , Erzo F. P. Luttmer, and Richard J. Zeckhauser, *Private Investment and Government Protection* number no. w12255. In 'NBER Working Paper Series.', Cambridge, Mass: National Bureau of Economic Research, 2006.

Laurent, Berge, "Efficient estimation of maximum likelihood models with multiple fixed-effects: the R package FENmlm," *CREA Discussion Papers*, 2018.

Levine, Jacob I, Brandon M Collins, Zachary L Steel, Perry de Valpine, and Scott L Stephens, "Higher Incidence of High-Severity Fire in and near Industrially Managed Forests," *Frontiers in Ecology and the Environment*, September 2022, *20* (7), 397–404.

Loveridge, Earl W., "The Fire Suppression Policy of the U. S. Forest Service," *Journal of Forestry*, August 1944, *42* (8), 549–554.

Lydersen, Jamie, Malcolm North, and Brandon Collins, "Severity of an Uncharacteristically Large Wildfire, the Rim Fire, in Forests with Relatively Restored Frequent Fire Regimes," *Forest Ecology and Management*, September 2014, *328*, 326–334.

Maximilian Auffhammer, Maya Duru, Edward Rubin, and David L. Sunding, "The Economic Impact of Critical-Habitat Designation: Evidence from Vacant-Land Transactions," *Land Economics*, March 2020, *96* (2), 188.

Miller, J. D., H. D. Safford, M. Crimmins, and A. E. Thode, "Quantitative Evidence for Increasing Forest Fire Severity in the Sierra Nevada and Southern Cascade Mountains, California and Nevada, USA," *Ecosystems*, February 2009, *12* (1), 16–32.

Miller, Kathleen A., "Climate Variability and Tropical Tuna: Management Challenges for Highly Migratory Fish Stocks," *Special Issue on Climate Change and Fisheries*, January 2007, *31* (1), 56–70.

Molitor, David, Jamie T. Mullins, and Corey White, "Air Pollution and Suicide in Rural and Urban America: Evidence from Wildfire Smoke," *Proceedings of the National Academy of Sciences*, September 2023, *120* (38), e2221621120. doi: 10.1073/pnas.2221621120.

Murphy, Kathy, Tim Rich, and Tim Sexton, "An Assessment of Fuel Treatment Effects on Fire Behavior, Suppression Effectiveness, and Structure Ignition on the Angora Fire," Technical Report, U.S. Department of Agriculture, Forest Service, Lake Tahoe Basin Management Unit 2007.

Nelson, Erik J., John C. Withey, Derric Pennington, and Joshua J. Lawler, "Identifying the Impacts of Critical Habitat Designation on Land Cover Change," *Resource and Energy Economics*, February 2017, *47*, 89–125.

NIFC, (National Interagency Fire Center), "Wildland Fire Incident Locations," 2024. https://www.wildfire.gov/application/fire-and-weather-data [Accessed: March 11, 2024].

North, Malcolm, April Brough, Jonathan Long, Brandon Collins, Phil Bowden, Don Yasuda, Jay Miller, and Neil Sugihara, "Constraints on Mechanized Treatment Significantly Limit Mechanical Fuels Reduction Extent in the Sierra Nevada," *Journal of Forestry*, January 2015, *113* (1), 40–48.

_ , Brandon M. Collins, and Scott Stephens, "Using Fire to Increase the Scale, Benefits, and Future Maintenance of Fuels Treatments," *Journal of Forestry*, October 2012, *110* (7), 392–401.

North, Malcolm P., Ryan E. Tompkins, Alexis A. Bernal, Brandon M. Collins, Scott L. Stephens, and Robert A. York, "Operational Resilience in Western US Frequent-Fire Forests," *Forest Ecology and Management*, March 2022, *507*, 120004.

Ott, Jeffrey E., Francis F. Kilkenny, and Theresa B. Jain, "Fuel Treatment Effectiveness at the Landscape Scale: A Systematic Review of Simulation Studies Comparing Treatment Scenarios in North America," *Fire Ecology*, February 2023, *19* (1), 10.

Plantinga, Andrew J., Randall Walsh, and Matthew Wibbenmeyer, "Priorities and Effectiveness in Wildfire Management: Evidence from Fire Spread in the Western United States," *Journal of the Association of Environmental and Resource Economists*, July 2022, *9* (4), 603–639. doi: 10.1086/719426.

Prichard, Susan J. and Maureen C. Kennedy, "Fuel Treatments and Landform Modify Landscape Patterns of Burn Severity in an Extreme Fire Event," *Ecological Applications*, April 2014, *24* (3), 571–590.

Pyne, Stephen J., *Year of the Fires: The Story of the Great Fires of 1910*, Missoula, Mont: Mountain Press Pub. Co, 2008.

Radeloff, V. C., David P. Helmers, Miranda H. Mockrin, Amanda R. Carlson, Todd J. Hawbaker, and Sebastián Martinuzzi, "The 1990-2020 Wildland-Urban Interface of the Conterminous United States - Geospatial Data (3rd Edition)," 2022. https://www.fs.usda.gov/rds/archive/catalog/RDS-2015-0012-3.

Radeloff, Volker C., David P. Helmers, H. Anu Kramer, Miranda H. Mockrin, Patricia M. Alexandre, Avi Bar-Massada, Van Butsic, Todd J. Hawbaker, Sebastián Martinuzzi, Alexandra D. Syphard, and Susan I. Stewart, "Rapid Growth of the US Wildland-Urban Interface Raises Wildfire Risk," *Proceedings of the National Academy of Sciences*, March 2018, *115* (13), 3314–3319. doi: 10.1073/pnas.1718850115.

Reilly, Matthew J., Mario Elia, Thomas A. Spies, Matthew J. Gregory, Giovanni Sanesi, and Raffaele Lafortezza, "Cumulative Effects of Wildfires on Forest Dynamics in the Eastern Cascade Mountains, USA," *Ecological Applications*, March 2018, *28* (2), 291–308.

REO, (Regional Ecosystem Office), "Land Use Allocations 2013," 2013. https://www.fs.usda.gov/r6/reo/library/maps.php [Accessed: April 17, 2023].

Richter, Clark, Marcel Rejmánek, Jesse E. D. Miller, Kevin R. Welch, JonahMaria Weeks, and Hugh Safford, "The Species Diversity × Fire Severity Relationship Is Hump-Shaped in Semiarid Yellow Pine and Mixed Conifer Forests," *Ecosphere*, October 2019, *10* (10), e02882.

Rideout, Douglas B., Yu Wei, Andy Kirsch, and Stephen J. Botti, "Toward a Unified Economic Theory of Fire Program Analysis with Strategies for Empirical Modeling," in Thomas P. Holmes, Jeffrey P. Prestemon, and Karen L. Abt, eds., *The Economics of Forest Disturbances: Wildfires, Storms, and Invasive Species*, Dordrecht: Springer Netherlands, 2008, pp. 361–380.

Romero, Frankie and James Menakis, "FIRE SEASON 2012: THE IMPACT OF FUEL TREATMENTS ON WILDFIRE OUTCOMES," *Fire Management Today*, 2013, *73* (2), 15–24.

Safford, H.D., J.T. Stevens, K. Merriam, M.D. Meyer, and A.M. Latimer, "Fuel Treatment Effectiveness in California Yellow Pine and Mixed Conifer Forests," *Forest Ecology and Management*, June 2012, *274*, 17–28.

Sánchez, José J., John Loomis, Armando González-Cabán, Douglas Rideout, and Robin Reich, "Do Fuel Treatments in U.S. National Forests Reduce Wildfire Suppression Costs and Property Damage?," *Journal of Natural Resources Policy Research*, June 2019, *9* (1), 42–73.

Schoennagel, Tania, Cara R. Nelson, David M. Theobald, Gunnar C. Carnwath, and Teresa B. Chapman, "Implementation of National Fire Plan Treatments near the Wildland–Urban Interface in the Western United States," *Proceedings of the National Academy of Sciences*, June 2009, *106* (26), 10706–10711.

_ , Jennifer K. Balch, Hannah Brenkert-Smith, Philip E. Dennison, Brian J. Harvey, Meg A. Krawchuk, Nathan Mietkiewicz, Penelope Morgan, Max A. Moritz, Ray Rasker, Monica G. Turner, and Cathy Whitlock, "Adapt to More Wildfire in Western North American Forests as Climate Changes," *Proceedings of the National Academy of Sciences*, May 2017, *114* (18), 4582–4590.

Sekhon, Jasjeet S., "Multivariate and Propensity Score Matching Software with Automated Balance Optimization: The Matching Package for R," *Journal of Statistical Software*, June 2011, *42* (7), 1–52.

Short, Karen C., "Spatial Wildfire Occurrence Data for the United States, 1992-2020 [FPA_FOD_20221014] (6th Edition)," 2023. https://www.fs.usda.gov/rds/archive/catalog/RDS-2013-0009.6.

Smith, V. Kerry, "Nonmarket Valuation of Environmental Resources: An Interpretive Appraisal," *Land Economics*, 1993, *69* (1), 1–26.

Spies, Thomas A, Jonathan W Long, Peter Stine, Susan Charnley, Lee Cerveny, Bruce G Marcot, Gordon Reeves, Paul F Hessburg, Damon Lesmeister, Matthew J Reilly, and Raymond J. Davis, "Chapter 12: Integrating Ecological and Social Science to Inform Land Management in the Area of the Northwest Forest Plan," Technical Report, In: Spies, T.A.; Stine, P.A.; Gravenmier, R.; Long, J.W.; Reilly, M.J., tech. coords. 2018. Synthesis of science to inform land management within the Northwest Forest Plan area. Gen. Tech. Rep. PNW-GTR-966. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station: 919-1020. 2018.

_ , _ , Susan Charnley, Paul F Hessburg, Bruce G Marcot, Gordon H Reeves, Damon B Lesmeister, Matthew J Reilly, Lee K Cerveny, Peter A Stine, and Martin G Raphael, "Twenty-Five Years of the Northwest Forest Plan: What Have We Learned?," *Frontiers in Ecology and the Environment*, November 2019, *17* (9), 511–520. https://doi.org/10.1002/fee.2101.

State of California, "California's Wildfire and Forest Resilience Action Plan," 2021.

Stephens, Scott L., Robert E. Martin, and Nicholas E. Clinton, "Prehistoric Fire Area and Emissions from California's Forests, Woodlands, Shrublands, and Grasslands," *Forest Ecology and Management*, November 2007, *251* (3), 205–216.

Stonesifer, Crystal S., David E. Calkin, Matthew P. Thompson, and Erin J. Belval, "Is This Flight Necessary? The Aviation Use Summary (AUS): A Framework for Strategic, Risk-Informed Aviation Decision Support," *Forests*, 2021, *12* (8).

Taylor, Michael H., Andrew J. Sanchez Meador, Yeon-Su Kim, Kimberly Rollins, and Hank Will, "The Economics of Ecological Restoration and Hazardous Fuel Reduction Treatments in the Ponderosa Pine Forest Ecosystem," *Forest Science*, December 2015, *61* (6), 988–1008.

Thomas, Jack Ward, Jerry E. Franklin, John Gordon, and K. Norman Johnson, "The Northwest Forest Plan: Origins, Components, Implementation Experience, and Suggestions for Change," *Conservation Biology: The Journal of the Society for Conservation Biology*, April 2006, *20* (2), 277–287.

Thompson, Matthew P., David E. Calkin, Jason Herynk, Charles W. McHugh, and Karen C. Short, "Airtankers and Wildfire Management in the US Forest Service: Examining Data Availability and Exploring Usage and Cost Trends," *International Journal of Wildland Fire*, 2013, *22* (2), 223.

_ , Nicole M. Vaillant, Jessica R. Haas, Krista M. Gebert, and Keith D. Stockmann, "Quantifying the Potential Impacts of Fuel Treatments on Wildfire Suppression Costs," *Journal of Forestry*, January 2013, *111* (1), 49–58.

Troy, Austin, "Chapter 8 A Tale of Two Policies: California Programs That Unintentionally Promote Development in Wildland Fire Hazard Zones," in Austin Troy and Roger G. Kennedy, eds., *Living on the Edge*, Vol. 6 of *Advances in the Economics of Environmental Resources*, Emerald Group Publishing Limited, January 2007, pp. 127–140.

USFS, (United States Forest Service), "Protecting People and Sustaining Resources in Fire Adapted Ecosystems: A Cohesive Strategy. Forest Service Response to General Accounting Office Report GAO-RCED-99-65.," Technical Report, United States Forest Service 2000.

_ , "Administrative Forest Boundaries," 2023.

_ , "National Forest System Roads," 2023. https://data.fs.usda.gov/geodata/edw/datasets.php [Accessed: April 6, 2023].

_ , "Ranger District Boundaries," 2023.

_ , "Hazardous Fuel Treatments - Polygon," 2024. https://data.fs.usda.gov/geodata/edw/datasets.php [Accessed: April 19, 2024].

_ **and State of California**, "Agreement for Shared Stewardship of California's Forests and Rangelands," 2020.

Vaillant, John, *Fire Weather: A True Story from a Hotter World*, first edition ed., New York: Alfred A. Knopf, 2023.

van Wagtendonk, Jan W., "The History and Evolution of Wildland Fire Use," *Fire Ecology*, December 2007, *3* (2), 3–17.

_ **, Kent A. van Wagtendonk, and Andrea E. Thode**, "Factors Associated with the Severity of Intersecting Fires in Yosemite National Park, California, USA," *Fire Ecology*, April 2012, *8* (1), 11–31.

Vazquez-Bare, Gonzalo, "Identification and Estimation of Spillover Effects in Randomized Experiments," *Journal of Econometrics*, November 2023, *237* (1), 105237.

Wagner, Katherine R. H., "Adaptation and Adverse Selection in Markets for Natural Disaster Insurance," *American Economic Journal: Economic Policy*, August 2022, *14* (3), 380–421.

_ , "Designing Insurance for Climate Change," *Nature Climate Change*, December 2022, *12* (12), 1070–1072.

Wang, Yuhan and David J. Lewis, "Wildfires and Climate Change Have Lowered the Economic Value of Western U.S. Forests by Altering Risk Expectations," *Journal of Environmental Economics and Management*, January 2024, *123*, 102894.

Wibbenmeyer, Matthew, Sarah E. Anderson, and Andrew J. Plantinga, "SALIENCE AND THE GOVERNMENT PROVISION OF PUBLIC GOODS," *Economic Inquiry*, July 2019, *57* (3), 1547–1567. https://doi.org/10.1111/ecin.12781.

Wimberly, Michael C., Mark A. Cochrane, Adam D. Baer, and Kari Pabst, "Assessing Fuel Treatment Effectiveness Using Satellite Imagery and Spatial Statistics," *Ecological Applications: A Publication of the Ecological Society of America*, September 2009, *19* (6), 1377–1384.

Yoder, J and P Ervin, "County-level effects of fuel treatments, WUI growth, and weather changes on wildfire acres burned suppression costs," *School of Economic Sciences, Washington State University*, 2012.

Appendix

A Model Results: A Two-Fire Example

In this section, we provide the derivations for the main results of our conceptual model presented in section 3. For clarity, we present the results for a system consisting of two fires; however, our results are easily generalized to a system with more fires (at the cost of additional notation).

Consider the system of equations associated with the first-order conditions for a two-fire problem:

$$\begin{aligned} G_1(E_1, \lambda, F_1) &= -L(X_1)\frac{\partial S(E_1, F_1)}{\partial E_1} - \frac{\partial C(E_1)}{\partial E_1} - \lambda = 0 \\ G_2(E_2, \lambda, F_2) &= -L(X_2)\frac{\partial S(E_2, F_2)}{\partial E_2} - \frac{\partial C(E_2)}{\partial E_2} - \lambda = 0 \\ G_3(E_1, E_2) &= E_1 + E_2 - \bar{E} = 0, \end{aligned}$$

where we've assumed that the resource constraint is binding—i.e., $\lambda > 0$. Linearizing this system, we have:

$$\begin{pmatrix} \frac{\partial G_1}{\partial E_1} & \frac{\partial G_1}{\partial E_2} & \frac{\partial G_1}{\partial \lambda} \\ \frac{\partial G_2}{\partial E_1} & \frac{\partial G_2}{\partial E_2} & \frac{\partial G_2}{\partial \lambda} \\ \frac{\partial G_3}{\partial E_1} & \frac{\partial G3}{\partial E_2} & \frac{\partial G_3}{\partial \lambda} \end{pmatrix} \begin{pmatrix} dE_1 \\ dE_2 \\ d\lambda \end{pmatrix} = - \begin{pmatrix} \frac{\partial G_1}{\partial F_1} & \frac{\partial G_1}{\partial F_2} \\ \frac{\partial G_2}{\partial F_1} & \frac{\partial G_2}{\partial F_2} \\ \frac{\partial G_3}{\partial F_1} & \frac{\partial G_3}{\partial F_2} \end{pmatrix} \begin{pmatrix} dF_1 \\ dF_2 \end{pmatrix}.$$

Suppose we are only interested in the comparative statics associated with a marginal change in F_1 holding F_2 constant. Then we can write this system as:

$$\begin{pmatrix} \partial E_1/\partial F_1 \\ \partial E_2/\partial F_1 \\ \partial \lambda/\partial F_1 \end{pmatrix} = - \begin{pmatrix} \frac{\partial G_1}{\partial E_1} & \frac{\partial G_1}{\partial E_2} & \frac{\partial G_1}{\partial \lambda} \\ \frac{\partial G_2}{\partial E_1} & \frac{\partial G_2}{\partial E_2} & \frac{\partial G_2}{\partial \lambda} \\ \frac{\partial G_3}{\partial E_1} & \frac{\partial G3}{\partial E_2} & \frac{\partial G_3}{\partial \lambda} \end{pmatrix}^{-1} \begin{pmatrix} \frac{\partial G_1}{\partial F_1} \\ \frac{\partial G_2}{\partial F_1} \\ \frac{\partial G_3}{\partial F_1} \end{pmatrix} = -H^{-1}x,$$

where H is the bordered Hessian.

Result 1. Fuel treatments will decrease fire suppression effort if and only if fuel treatments and suppression effort are q-substitutes. In contrast, fuel treatments will increase fire suppression effort if and only if fuel treatments and suppression effort are q-complements.

Proof. Let H_1 denote the bordered Hessian H with the first column replaced by the vector x.

Applying Cramer's rule, we have:

$$\begin{aligned}\frac{\partial E_1}{\partial F_1} &= -\frac{\det(H_1)}{\det(H)} \\ &= -\frac{-L(X_1)\cdot\dfrac{\partial^2 S(E_1,F_1)}{\partial F_1 \partial E_1}}{\det(H)}.\end{aligned}$$

Given our assumptions regarding the convexity of suppression costs $C(E)$ and fire size $S(E,F)$, the bordered Hessian H is negative definite, and thus $\det(H) < 0$. Therefore,

$$\frac{\partial E_1}{\partial F_1} < 0 \iff -\frac{\partial^2 S(E_1,F_1)}{\partial F_1 \partial E_1} < 0$$

and

$$\frac{\partial E_1}{\partial F_1} > 0 \iff -\frac{\partial^2 S(E_1,F_1)}{\partial F_1 \partial E_1} > 0,$$

where $-\frac{\partial^2 S(E_1,F_1)}{\partial F_1 \partial E_1} < 0$ if fuel treatments and suppression effort are q-substitutes and $-\frac{\partial^2 S(E_1,F_1)}{\partial F_1 \partial E_1} > 0$ if they are q-complements. □

Corollary 1.1. Fuel treatments will decrease fire suppression costs if and only if fuel treatments and suppression effort are q-substitutes. In contrast, fuel treatments will increase fire suppression costs if and only if fuel treatments and suppression effort are q-complements.

Proof.

$$\frac{\partial C(E_1)}{\partial F_1} = \frac{\partial C(E_1)}{\partial E_1}\cdot\frac{\partial E_1}{\partial F_1} < 0 \iff \frac{\partial E_1}{\partial F_1} < 0 \iff -\frac{\partial^2 S(E_1,F_1)}{\partial F_1 \partial E_1} < 0.$$

□

Corollary 1.2. Fuel treatments will decrease fire size if fuel treatments and suppression effort are q-complements. In contrast, fuel treatments may or may not decrease fire size if fuel treatments and suppression effort are q-substitutes.

Proof.

$$\frac{dS(E_1,F_1)}{dF_1} = \frac{\partial S(E_1,F_1)}{\partial E_1}\cdot\frac{\partial E_1}{\partial F_1} + \frac{\partial S(E_1,F_1)}{\partial F_1},$$

which is negative if $\frac{\partial E_1}{\partial F_1} > 0$ (i.e., if fuel treatments and suppression effort are q-complements) but indeterminate if $\frac{\partial E_1}{\partial F_1} < 0$ (i.e., if fuel treatments and suppression effort are q-substitutes) since $\frac{\partial S(E_1,F_1)}{\partial E_1}$ and $\frac{\partial S(E_1,F_1)}{\partial F_1}$ are assumed to be negative. □

Result 2. Fuel treatments will induce spillovers onto other fires if the suppression effort resource constraint binds. Specifically, fuel treatments will draw suppression effort away from other fires if they are q-complements and direct suppression effort toward other fires if they are q-substitutes.

Proof. Let H_2 denote the bordered Hessian H with the second column replaced by the vector x. Applying Cramer's rule, we have:

$$\begin{aligned}\frac{\partial E_2}{\partial F_1} &= -\frac{\det(H_2)}{\det(H)} \\ &= -\frac{L(X_1)\cdot \dfrac{\partial^2 S(E_1,F_1)}{\partial F_1 \partial E_1}}{\det(H)}.\end{aligned}$$

Given the negative definiteness of the bordered Hessian H, $\det(H) < 0$. Therefore,

$$\frac{\partial E_2}{\partial F_1} > 0 \iff -\frac{\partial^2 S(E_1,F_1)}{\partial F_1 \partial E_1} < 0$$

and

$$\frac{\partial E_2}{\partial F_1} < 0 \iff -\frac{\partial^2 S(E_1,F_1)}{\partial F_1 \partial E_1} > 0,$$

where $-\frac{\partial^2 S(E_1,F_1)}{\partial F_1 \partial E_1} < 0$ if fuel treatments and suppression effort are q-substitutes and $-\frac{\partial^2 S(E_1,F_1)}{\partial F_1 \partial E_1} > 0$ if they are q-complements. □

Corollary 2.1. Fuel treatments may increase or decrease total fire suppression costs, regardless of whether fuel treatments are q-complements or q-substitutes.

Proof.

$$\begin{aligned}\frac{\partial[\sum_i C(E_i)]}{\partial F_1} &= \frac{\partial C(E_1)}{\partial E_1}\cdot\frac{\partial E_1}{\partial F_1} + \frac{\partial C(E_2)}{\partial E_2}\cdot\frac{\partial E_2}{\partial F_1} \\ &= \frac{\partial E_1}{\partial F_1}\cdot\left(\frac{\partial C(E_1)}{\partial E_1} - \frac{\partial C(E_2)}{\partial E_2}\right),\end{aligned}$$

where the second equality follows from the fact that $\frac{\partial E_1}{\partial F_1} = -\frac{\partial E_2}{\partial F_1}$ (from Results 1 and 2). Thus, regardless of the sign of $\frac{\partial E_1}{\partial F_1}$, the sign of the expression above depends on whether $\frac{\partial C(E_1)}{\partial E_1} > \frac{\partial C(E_2)}{\partial E_2}$ or $\frac{\partial C(E_1)}{\partial E_1} < \frac{\partial C(E_2)}{\partial E_2}$. □

Corollary 2.2. If the effort resource constraint does not bind, fuel treatments will decrease total fire suppression costs if and only if fuel treatments and fire suppression efforts are q-substitutes.

Proof. If the effort resource constraint does not bind, then $\lambda = 0$ and $\frac{\partial E_2}{\partial F_1} = 0$. Thus,

$$\frac{\partial[\sum_i C(E_i)]}{\partial F_1} = \frac{\partial C(E_1)}{\partial E_1}\cdot\frac{\partial E_1}{\partial F_1} < 0 \iff \frac{\partial E_1}{\partial F_1} < 0.$$

□

Result 3. Fuel treatments increase the value of a fire manager's economic program provided the direct effect of fuel treatments on fire size is negative.

Proof. Let $V(F_1, F_2)$ denote the value function of a fire manager's program evaluated at the optimal allocation of suppression effort. Then, using the envelope theorem, the marginal value of a fuel treatment that intersects with a fire is:

$$\frac{\partial V(F_1, F_2)}{\partial F_1} = -L(X_1) \cdot \frac{\partial S(E_1, F_1)}{\partial F_1} > 0 \iff \frac{\partial S(E_1, F_1)}{\partial F_1} < 0.$$

□

B Land Managers Optimal Fuel Treatment Allocation Problem

In this section, we formally demonstrate that the effect of fuel treatments on suppression costs and fire size that we identify empirically is only a portion of the total effect they may have across the landscape. To do so, we depict a land manager who chooses the optimal allocation of fuel treatment across the landscape to minimize the sum of expected suppression costs and damages from wildfires. For simplicity, suppose there is a probability of ignition on $i = 1, \ldots, N$, identical plots of land. The probability of a fire occurring on that plot of land is a function of fuel treatments in that area: $\pi_i(F_i)$. Further suppose that, conditional on a fire occurring on plot i, the expected size of the fire, S_i, depends not only on fuel treatments on plot i, F_i, but also fuel treatments further away from the fire on other plots of land, F_{-i}. As in Rideout et al. (2008), we assume that damages from wildfires (property losses, timber, etc.) are proportional to fire size: $L_i(X_i)S_i(F_1, \ldots, F_N)$ where losses, L_i are a function of assets at risk, X_i.

Given an objective of conducting fuel treatments to minimize the expected damages and fire suppression costs across the landscape subject to a budget constraint, we can write the optimization problem as:

$$\max_{F_1,\ldots,F_N} -\sum_{i=1}^{N} \pi_i(F_i) \left[L_i(X_i)S_i(F_1, \ldots, F_N) + SC_i(F_1, \ldots, F_N)\right]$$

$$\text{s.t. } \sum_{i}^{N} c_i(F_i) \leq B,$$

where $c_i(F_i)$ is the cost of conducting F_i units of fuel treatment on plot i and B is the fixed amount of resources that can be devoted to conducting fuel treatments. Letting λ denote the Lagrange multiplier associated with the budget constraint, the necessary first-order conditions are:

$$\frac{\partial \mathcal{L}}{\partial F_i} = \underbrace{-\pi_i'(F_i)\left[L_i(X_i)S_i(F_1,\ldots,F_N) + SC_i(F_1,\ldots,F_N)\right]}_{\text{Ignition Effect}}$$
$$\underbrace{-\pi_i(F_i)\left[L_i(X_i)\frac{\partial S_i(F_1,\ldots,F_N)}{\partial F_i} + \frac{\partial SC_i(F_1,\ldots,F_N)}{\partial F_i}\right]}_{\text{Prevention Effect}}$$
$$\underbrace{-\sum_{j\neq i}\pi_j(F_j)\left[\frac{L_j(X_j)\partial S_j(F_1,\ldots,F_N)}{\partial F_i} + \frac{\partial SC_j(F_1,\ldots,F_N)}{\partial F_i}\right]}_{\text{Landscape Effect}} = c_i'(F_i)\ \forall i = 1,\ldots,N$$

The first term, which we call the "ignition effect," represents the effect of fuel treatments from reducing the likelihood that fires ignite on a parcel of land ($\pi_i'(F_i) < 0$). The second term, which we call the "prevention effect," represents how suppression costs and the size of fires are influenced by the proximity of fuel treatments close to the ignition point of a fire. The third term, which we call the "landscape effect," represents the effect of fuel treatments on the spread of wildfires across the landscape. That is, if there exists parcels of land i and j such that $\frac{L_j(X_j)\partial S_j(F_1,\ldots,F_N)}{\partial F_i} + \frac{\partial SC_j(F_1,\ldots,F_N)}{\partial F_i} < 0$, then fuel treatments will influence the cost and size of large fires, which spread into fuel treatments that occur further from their ignition point.

Our empirical analysis only identifies the prevention effect since we are conditioning on fires that ignite close to fuel treatments. If the ignition and landscape effects of fuel treatments are significant, then our estimates are only capturing a portion of the total benefits that arise from fuel treatments. We leave the identification of the ignition and landscape effects to future research.

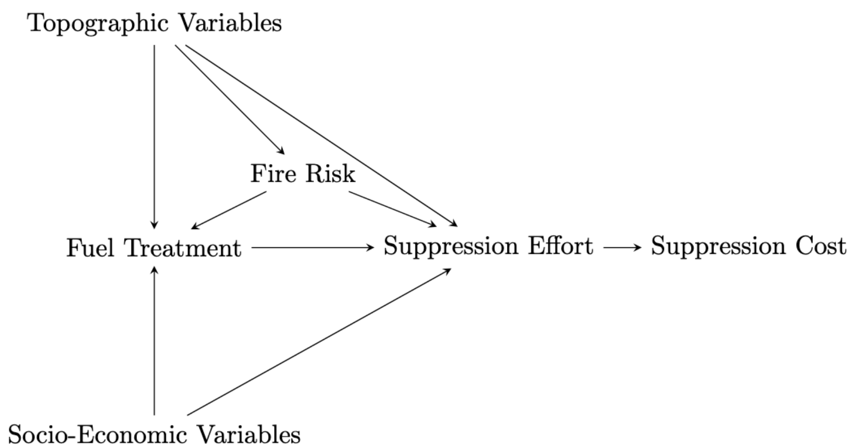
C The Data Generating Process for Fuel Treatments & Fire Suppression Costs

Figure S.1 presents a visual representation of the hypothesized data-generating process for fuel treatments and fire suppression costs, both of which are a function of topographic, socio-economic, and fire risk variables. The endogenous decision of both the land manager choosing the optimal location of fuel treatments and the fire manager allocating fire suppression effort results in jointly determined fuel treatment locations and fire suppression costs.[42]

The objective of land managers, who decide the location of fuel treatments, is often to maximize the effectiveness of treatments at protecting assets at risk while minimizing the costs of treatment. As a result, fuel treatments are typically located close to homes and other assets at risk (socio-economic variables) while occurring in areas where fire is more likely to occur or spread (fire risk). Because resources for land managers are limited, fuel treatments typically occur in areas where the costs of fuel treatment are minimized and, as a result, typically occur closer to forest service roads

[42]See Appendix B for an overview of the land manager's fuel treatment location problem and section 3 for the fire manager's fire allocation problem.

Figure S.1: The Data generating process for Fuel Treatments & Fire Suppression Costs



and at lower elevations and slopes (topographic variables).

The objective of a fire manager, who is tasked with deciding the allocation of fire suppression effort across multiple fires burning simultaneously, is to minimize the sum of fire suppression costs and damages from wildfires. As a result, more fire suppression effort is spent on fighting fires closer to homes and other assets at risk relative to fires occurring further away from such assets. Topography and fire weather also influence the cost of fighting a given fire because fires that occur in inaccessible terrain require more expensive resources to suppress the fire (e.g., smoke jumpers or aerial attack) while fires that occur in extreme weather conditions (fire risk) require more time and effort to suppress.

An estimation strategy that controls for all the relevant factors determining fuel treatments and fire suppression costs may still suffer from bias because assets at risk (e.g., homes) and fire risk are imperfectly measured, resulting in omitted factors that determine both fuel treatments and fire suppression effort. In particular, we expect home proximity and fire risk to be positively correlated with fire suppression effort and fuel treatments because of the influencing factors discussed above. Thus, any estimation strategy that compares fires that occur close to fuel treatments with fires that do not will likely suffer from an upward bias (i.e., the expected negative effect of fuel treatments on suppression costs will be understated.). This motivates our use of an instrument that does not correlate with socio-economic and fire risk characteristics.

D The Intersection-Union Hypothesis Test

Our model of the fire manager's effort allocation problem demonstrates that a negative direct effect of fuel treatments on fire size is a sufficient statistic for the economic benefits of fuel treatments. We test for its existence indirectly by testing the null hypothesis that the effects of fuel treatments on fire size or cost are weakly positive. Specifically, let ϕ_c and ϕ_s denote the elasticity of suppression costs and fire size with respect to fuel treatments. We want to test the null hypothesis

$$H_o : \phi_c \geq 0 \text{ or } \phi_s \geq 0$$

against the alternative hypothesis of

$$H_a : \phi_c < 0 \text{ and } \phi_s < 0.$$

The intersection-union hypothesis test (Casella and Berger, 2002) considers the overall null hypothesis of the union of several individual null hypotheses to be true if at least one of the individual null hypotheses is true. Thus, to reject the null, we must have both $\phi_c < 0$ and $\phi_s < 0$. This suggests the following implementation:

1. Conduct a one-side test for $\phi_c \geq 0$ and a one-sided test for $\phi_s \geq 0$.
2. Reject overall H_o if both of the one-sided tests for ϕ_c and ϕ_s are rejected.

We implement this hypothesis test using a bootstrap approach that adapts the percentile-t bootstrap with asymptotic refinement procedure presented in Cameron and Trivedi (2005). Specifically, we bootstrap the following t-statistics:

$$t_c = \frac{\hat{\phi}_c - \phi_{c0}}{se(\hat{\phi}_c)} \quad \text{and} \quad t_s = \frac{\hat{\phi}_s - \phi_{s0}}{se(\hat{\phi}_s)},$$

where $\hat{\phi}_c$ and $\hat{\phi}_s$ are our instrumental variable estimates and $\phi_{c0} = 0$ and $\phi_{s0} = 0$ are the values under the null hypothesis. The bootstrap views the original sample as the data generating process (dgp), so the bootstrap sets the dgp values of ϕ_c and ϕ_s to be $\hat{\phi}_c$ and $\hat{\phi}_s$. In each bootstrap resample, we compute the following t-statistics:

$$t^*_{c,b} = \frac{\hat{\phi}^*_{c,b} - \hat{\phi}_c}{se(\hat{\phi}^*_{c,b})} \quad \text{and} \quad t^*_{s,b} = \frac{\hat{\phi}^*_{s,b} - \hat{\phi}_s}{se(\hat{\phi}^*_{s,b})},$$

where $\hat{\phi}^*_{c,b}$ and $\hat{\phi}^*_{s,b}$ are the parameter estimates in the bth bootstrap and $se(\hat{\phi}^*_{c,b})$ and $se(\hat{\phi}^*_{s,b})$ are the estimates of the standard error of $\hat{\phi}^*_{c,b}$ and $\hat{\phi}^*_{s,b}$ using the same method (i.e., cluster-robust) as the computation of $se(\hat{\phi}_c)$ and $se(\hat{\phi}_s)$.

The B bootstraps yield the t-values $t^*_{c,1}, ..., t^*_{c,B}$ and $t^*_{s,1}, ..., t^*_{s,B}$, whose empirical joint distribution is used as the estimate of the joint distribution of t_c and t_s. The p-value for the overall hypothesis test is the probability of observing values of the test statistics as extreme as t_s and t_s under the null hypothesis. We can calculate the empirical p-value as the proportion of bootstrap samples in which both t-statistics lie below their observed values:

$$p = \frac{\sum_{b=1}^{B} \mathbf{1}(t^*_{c,b} < t_c \text{ and } t^*_{s,b} < t_s)}{B}.$$

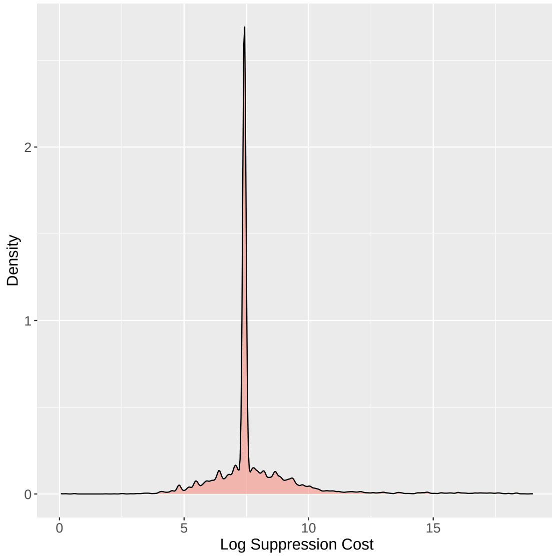
We reject the null if $p < \alpha$, where $1 - \alpha$ is the confidence level of the test. Given the clustered nature of our data, we conduct the bootstrap sampling by drawing independent clusters of fires (with replacement).

E Land-Use Allocations Under The NWFP

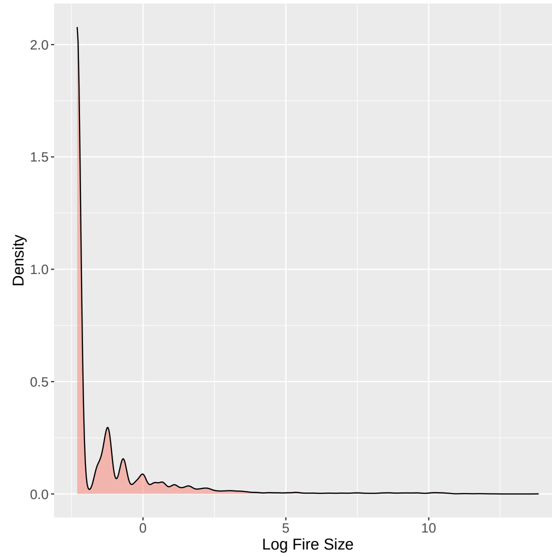
Thirty percent of the NWFP area comprises of a network of late-successional reserves (LSRs) designed to protect remaining old-growth forests and habitat for the NSO and marbled murrelet. Another thirty percent of NWFP area is comprised of "Congressionally Reserved" (CR) areas, areas such as National Parks or wilderness areas. Riparian reserves – areas designed to protect and restore salmonid habitat – comprise another 11 percent of the NWFP area. In both LSRs and riparian reserves fuel treatment activity is possible though limited due to potential for litigation's and management restrictions. However, in a good portion of CR areas, such as wilderness areas, fuel treatment is not allowed. Non-reserved "matrix" lands, are regions in which the majority of timber harvest and other silvicultural activities take place comprises 16 percent of NWFP area See Figure 1 for a map of NWFP areas and Table S.1 for a list of and description of all land allocations under the plan.

F Supplementary Figures

Figure S.2: Distribution of fire suppression costs and fire size.



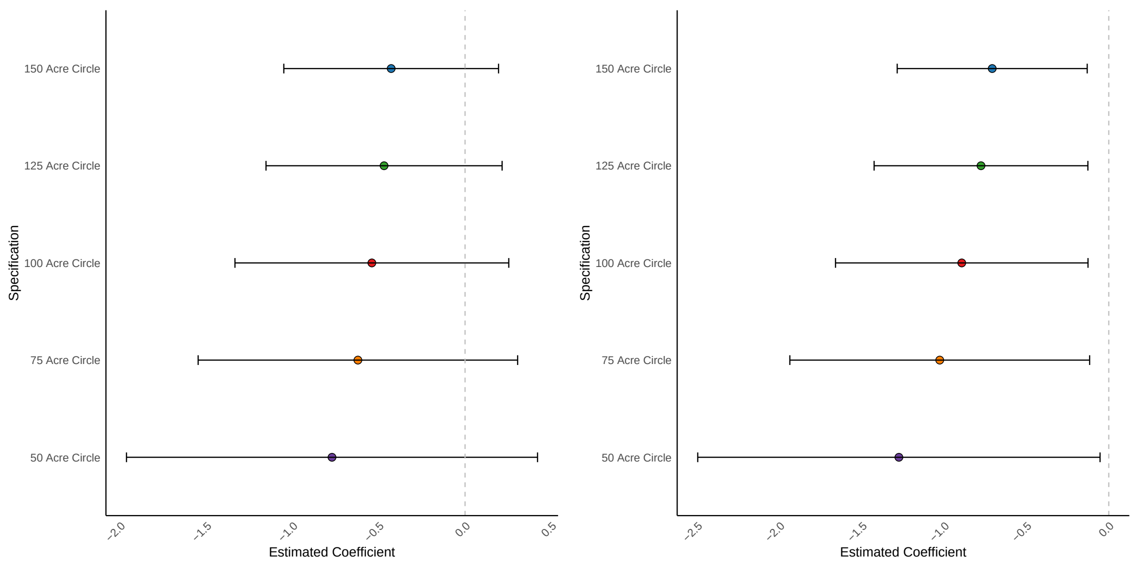
(a) Log Suppression Costs



(b) Log Fire Size

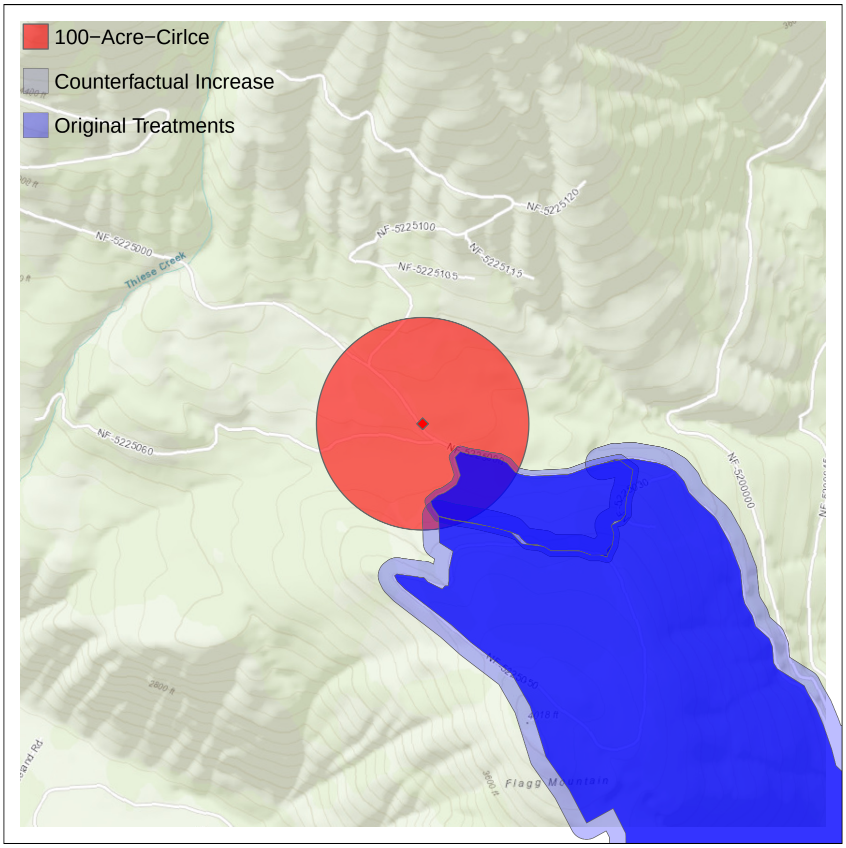
Figure S.3: IV estimates by fuel treatment acre circle size

(a) Fire Size (b) Suppression Costs



The above figures plot the IV suppression cost and fire size estimates based on different specifications of fire fuel treatment acre circle size.

Figure S.4: Example Counterfactual Increases in Fuel Treatments - Flagg Mountain Fire - 2020



The above map visually demonstrates how fuel treatments are scaled up proportionately in our counterfactual analysis for a particular fire, the Flagg Mountain Fire, a 0.1 acre fire which occurred close to Mazama WA in 2020. The red star shows the ignition point location, the red circle is area from which fuel treatments are to be calculated (in this case 100-Acres surrounding the ignition point) and the dark blue shows the original location of fuel treatments close to the fire. The light blue areas are the counterfactual increased area that receives fuel treatment. In our counterfactual analysis we recalculate the total acres intersected with the fire to garner an estimated increase in 100-acre fire-fuel treatment intersections. To avoid double counting we take the union of fuel treatments within the circle and count mechanical and prescribed fire treatments separately as before.

G Supplementary Tables

Table S.1: Land allocations under the Northwest Forest Plan

Land Allocation	Description	Acres	% NWFP
Late-Successional Reserves (LSRs)	Lands reserved for the protection and restoration of old growth forest ecosystems and habitat for marbled murrelet (LSR3) and northern spotted owl activity core reserves (LSR4).	7.4 mil	30%
Congressional Reserved (CR) Areas	Lands reserved by the U.S. Congress such as wilderness areas, wild and scenic rivers, and national parks and monuments.	7.3 mil	30%
Riparian Reserves	Protective buffers along streams, lakes, and wetlands designed to enhance habitat for riparian-dependent organisms, provide good water-quality dispersal corridors for terrestrial species, and provide connectivity within watersheds.	2.6 mil	11%
Matrix	Federal lands outside of reserved allocations where most timber harvest and silvicultural activities were expected to occur.	4 mil	16%
Administrative Withdrawn Areas	Areas identified in local forest and district plans; they include recreation and visual areas, back country, and other areas where management emphasis does not include scheduled timber harvest.	1.5 mil	6%
Adaptive Management Areas–nonreserved	Identified to develop and test innovative management to integrate and achieve ecological, economic, and other social and community objectives. Some commercial timber harvest was expected to occur in these areas, but with ecological objectives.	1.5 mil	6%
Managed Late-Successional Areas	Areas for the restoration and maintenance of optimum levels of old growth stands on a landscape scale, where regular and frequent wildfires occur. Silvicultural and fire hazard reduction treatments are allowed to help prevent older forest losses from large wildfires.	.1 mil	$< 1\%$

Table S.2: Main Variables & Data Sources

Category	Variables	Sources
Fires	Cost per fire, Acres Burned & Ignition Date	FAMWEB (2023) NIFC (2024)
Fuel Treatments	Acres treated, cost, & treatment type	USFS (2024)
Institutional Variables	NWFP Land-use Designations	REO (2013)
Topography	Slope, Aspect, & Elevation	LANDFIRE
Weather	Temperature, Precipitation, Vapor Pressure Deficit Wind Speed & ERC	PRISM GridMET
Vegetation Characteristics	Fuel Group Type Previous Acres Burned	LANDFIRE
Historic Fire Risk	Mean Fire Return Interval (MFRI) Climate Normals	LANDFIRE PRISM
Economic Variables	Distance to WUI Cenus Block, Number of Households & Population Total housing value, total household income Forest Service Roads	Radeloff et al. (2022) ACS USFS (2023b)

Table S.3: Control Variable Names, Descriptions, & Sources

Name	Definition	Source
Topographic Variables		
Slope	Slope percent at origin of ignition	LANDFIRE
Elevation	Elevation (ft) at origin of ignition	LANDFIRE
Aspect Class	8 aspect classes based on the cardinal directions[43]	LANDFIRE
TRI	Terrain Ruggedness Index (TRI)[44]	LANDFIRE
Weather		
Temperature Max	Maximum temperature on day of discovery and point of ignition	PRISM
Temperature Mean	Mean temperature on day of discovery and point of ignition	PRISM
VPD	Max vapor pressure deficit on day of discovery and point of ignition	PRISM
Wind Speed	Average wind speed meter/second on day of discovery and point of ignition	gridMET
ERC	Average energy release component (ERC) on day of discovery and point of ignition	gridMET
Vegetation Characteristics		
Previous Acres Burned	The number of acres previously burned inside of the 100-acre ignition circle within the last 10 years	MTBS
Riparian	Dummy variable equal to one if the existing vegetation group type associated with the point of ignition is Riparian	LANDFIRE
Fuel Group Type	The fuel group type associated with a fires ignition point in 2001 based on the 13 Anderson Fire Behavior Fuel Model	LANDFIRE
Canopy Bulk Density	The density of available canopy fuel in a stand based on a fires ignition point in 2001. Measurements are kg m-3 * 100.	LANDFIRE

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[43]See https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/how-aspect-works.htm for the classes used.

[44]Constructed using the elevation layer from LANDFIRE and then using the terrain function from terra.

Table S.3 Continued

Name	Definition	Source
Canopy Bulk Density	The average height of the top of the vegetated canopy based on a fires ignition point in 2001. Measurement units are meters * 10	LANDFIRE
Canopy Base Height	The average height from the ground to a forest stand's canopy bottom based on a fires ignition point in 2001. Measurement units are meters*10	LANDFIRE
Determinants of Fire Suppression Effort		
Distance WUI	Distance from ignition to nearest U.S. Census WUI Block	Radeloff et al. (2022)
Distance USFS Road	Distance from ignition to nearest USFS road	USFS (2023b)
Total Housing Value	The total housing value in 10 kilometer radius from point of ignition/100,000	ACS
Total Population	The total population within 10 kilometers of ignition point based on 2010 US Census Blocks (assuming uniform distribution)	(Radeloff et al., 2022)
Total Housing Units	The total housing units within 10 kilometers of ignition point based on 2010 US Census Blocks (assuming uniform distribution)	(Radeloff et al., 2022)
Historic Fire Risk Variables		
MFRI	Mean Fire Return Interval (MFRI), the average period between fires under presumed historical fire regime	LANDFIRE
Precip - CN	Precipitation 30 year (1991-2020) climate normal. Calculated as the average monthly precipitation in August based on the ignition point of a fire	PRISM
Temp Mean - CN	Temperature Mean 30 year (1991-2020) climate normal. Calculated as the average monthly temperature mean in August based on the ignition point of a fire	PRISM
Temp Max - CN	Temperature Max 30 year (1991-2020) climate normal. Calculated as the average monthly temperature max in August based on the ignition point of a fire	PRISM

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Table S.3 Continued

Name	Definition	Source
VPD - CN	Max Vapor Pressure Deficit 30 year (1991-2020) climate normal. Calculated as the average monthly temperature max vapor pressure deficit in August based on the ignition point of a fire	PRISM
Administrative Units		
National Forest	Dummy variables for National Forest	USFS (2023a)
Ranger District	Dummy variables for Ranger District (subset of National Forest)	USFS (2023c)

Table S.4: IV Matching Estimate Results

	Log Fire Size - LSR IV	Log Fire Cost - LSR IV
Point Estimate	-0.598	-0.716
95% CI	[-1.139,-0.058]	[-1.204,-0.227]
N	6548	6548

Above shows the IV estimate using matching. Fires are matched via a mixed exact and inexact matching using Genetic Search Algorithm (the GenMatch function from the Matching package in R (Sekhon, 2011)): i) fires are exactly matched such that they occur in the same National Forest during the same month (of year) and have the same existing vegetation group type, ii) fires are inexactly matched to find the optimal covariate balance across the most important determinants of fire suppression costs and fire size: Distance to WUI and FS road, elevation and slope (at ignition point), and VPD and wind speed (on day of ignition). Standard errors are calculated via the Delta Method.

Table S.5: LSR IV - Robustness Check - Spillovers

	First Stage	**Reduced Form**		**IV**		**OLS**	
	$\log(FT_{it})$	**Size**	**Cost**	**Size**	**Cost**	**Size**	**Cost**
LSR_i	-0.137***	0.048	0.113**				
	(0.026)	(0.057)	(0.041)				
$\log(FT_{it})$				-0.346	-0.825*	-0.040**	-0.025
				(0.434)	(0.407)	(0.014)	(0.015)
No. Fires	0.000	0.001**	0.002***	0.001***	0.002***	0.001**	0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
No. Fires FT > 0	-0.004	0.012	0.002	0.010	-0.001	0.011	0.002
	(0.003)	(0.011)	(0.009)	(0.011)	(0.009)	(0.011)	(0.009)
1st Stage F-Stat	27.3						
R2	0.19	0.14	0.15	0.11	-0.04	0.14	0.15
N	8407	8407	8407	8407	8407	8407	8407

* p < 0.1, ** p < 0.05, *** p < 0.01

The above table explores the robustness of the main IV regression results when adding controls that measure the scarcity of suppression resources: "No. Fires" and "No. Fires FT > 0". "No. Fires" is the difference in the average number of fires occurring in a state from 2000-2020 to the realized number of co-occurring fires in the state where a fire ignites, while "No. Fires FT > 0" is the number of fires that have a non-zero fuel treatment-100 acre intersection occurring in the same state where a fire ignites. The table reports the results of five separate regressions for the first stage, reduced form, and full IV estimate results using an indicator for whether a fire occurs within a late-successional reserve, LSR_i as an instrument for the natural log of fuel treatments $\log(FT_{it})$. The sample includes wildfires in 17 National Forests that are apart of the NWFP from 2006–2020. The first column reports the coefficient estimates for the first stage, $\log(FT_{it})$, while the second and third columns are the reduced form results on the natural log of fire size and suppression costs. The fourth and fifth columns are the full 2SLS regression results on the natural log of wildfire size and suppression cost. Each regression includes the same control variables and fixed effects described in Table 3. Standard errors are clustered at the national-forest level. First stage F-statistics are calculated via cluster robust-standard errors from the Fixest package in R.

Table S.6: LSR IV - Robustness Checks - Estimation On Different Subsamples

	1st Stage	RF Size	RF Cost	IV Size	IV Cost
Lightning Only Fires					
LSR_i	-0.150***	0.156*	0.199***		
	(0.041)	(0.078)	(0.054)		
$\log(FT_{it})$				-1.043	-1.325**
				(0.677)	(0.591)
1st Stage F-Stat	13.5				
N	5052	5052	5052	5052	5052
All NWFP National Forests					
LSR_i	-0.105***	0.069	0.123**		
	(0.028)	(0.052)	(0.049)		
$\log(FT_{it})$				-0.658	-1.176*
				(0.541)	(0.577)
1st Stage F-Stat	42.5				
N	18722	18722	18722	18722	18722
$<$ 2km from Matrix-LSR Border					
LSR_i	-0.106***	0.026	0.095		
	(0.019)	(0.067)	(0.056)		
$\log(FT_{it})$				-0.245	-0.893
				(0.621)	(0.573)
1st Stage F-Stat	11.5				
N	7904	7904	7904	7904	7904
No Complex Fires					
LSR_i	-0.174***	0.102	0.091**		
	(0.044)	(0.062)	(0.034)		
$\log(FT_{it})$				-0.583	-0.521**
				(0.358)	(0.198)
1st Stage F-Stat	15.8				
N	4732	4732	4732	4732	4732

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The above table explores the robustness of the main IV regression results when using different samples of fires. The table reports the results of five separate regressions for the first stage, reduced form, and full IV estimate results using an indicator for whether a fire occurs within a late-successional reserve, LSR_i as an instrument for the natural log of fuel treatments $\log(FT_{it})$. Each regression includes the controls and fixed effects used in Table 3. The first sample includes only fires started by lightning, the second fires that start inside of Matrix and LSRs within all 17 NWFP National Forests. The third sample uses only fires that are within 2 kilometers of Matrix-LSR borders. The fourth sample only includes fires that not apart of a complex from the NIFC fire cost data source (2015-2023). Standard errors are clustered at the national forest level. First stage F-statistics are calculated via cluster robust-standard errors from the Fixest package in R.

Table S.7: LSR IV - Robustness Checks - Changes to Dependent Variable

	1st Stage	RF Size	RF Cost	IV Size	IV Cost
No Zero Cost Fires					
LSR_i	-0.112***	0.057	0.120*		
	(0.032)	(0.069)	(0.065)		
$\log(FT_{it})$				-0.506	-1.074
				(0.661)	(0.774)
1st Stage F-Stat	12.1				
N	5380	5380	5380	5380	5380
Above Median Size & Cost					
LSR_i	-0.137***	0.018	0.011**		
	(0.021)	(0.014)	(0.005)		
$\log(FT_{it})$				-0.133	-0.082*
				(0.098)	(0.039)
1st Stage F-Stat	42.5				
N	9923	9923	9923	9923	9923
Average Burn Severity					
LSR_i	-0.150***	0.056**	-		
	(0.041)	(0.021)	-		
$\log(FT_{it})$				-0.375*	-
				(0.211)	-
1st Stage F-Stat	13.5				
N	5052	5052	-	5052	-

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The above table explores the robustness of the main IV regression results to different outcomes of interest. The table reports the results of five separate regressions for the first stage, reduced form, and full IV estimate results using an indicator for whether a fire occurs within a late-successional reserve, LSR_i as an instrument for the natural log of fuel treatments $\log(FT_{it})$. Each regression includes the same instrument, controls, and fixed effects used in Table 3. The first set of regressions removes all zero cost fires from our sample where previously all small fires were replaced with the median cost of suppressing non-zero fires. The second set of regressions replaces the natural log of fire size and suppression costs for indicators of whether a fire is above the median size or cost. The third set of regressions replaces the natural log of fire size with the average burn severity within the 100-acre circle of a fire. Standard errors are clustered at the national forest level. First stage F-statistics are calculated via cluster robust-standard errors from the Fixest package in R.

Table S.8: LSR IV - Robustness Checks - Changes to Instrument & Endogenous Regressors

	1st Stage	RF Size	RF Cost	IV Size	IV Cost
Linear Fuel Treatments: FT_{it}					
LSR_i	-1.762***	0.074	0.122**		
	(0.494)	(0.055)	(0.045)		
FT_{it}				-0.042	-0.069*
				(0.035)	(0.037)
1st Stage F-Stat	10.3				
R^2	0.14	0.13	0.13	0.03	-0.21
N	9923	9923	9923	9923	9923
IVHS Fuel Treatments					
LSR_i	-0.164***	0.074	0.122**		
	(0.025)	(0.055)	(0.045)		
$ashin(FT_{it})$				-0.452	-0.748**
				(0.338)	(0.324)
1st Stage F-Stat	43.7				
N	9923	9923	9923	9923	9923
Previous 5 Years Fuel Treatments					
LSR_i	-0.076***	0.074	0.122**		
	(0.013)	(0.055)	(0.045)		
$\log(FT_{it,5Y})$				-0.976	-1.613**
				(0.743)	(0.720)
1st Stage F-Stat	35.1				
N	9923	9923	9923	9923	9923
Continuous IV					
$AcresLSR_i$	-0.014***	0.009	0.014***		
	(0.002)	(0.006)	(0.005)		
$\log(FT_{it})$				-0.640	-0.998**
				(0.403)	(0.424)
1st Stage F-Stat	41.5				
N	9923	9923	9923	9923	9923

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The above table explores the robustness of the main IV regression results to different specifications of the endogenous variable and instrument. The table reports the results of five separate regressions for the first stage, reduced form, and full IV estimate results using different instruments and endogenous regressors. Each regression includes the same sample, controls, and fixed effects used in Table 3. The first set of regressions replaces the natural log of fuel treatments, $\log(FT_{it})$, for fuel treatments in levels FT_{it}. The second set of regressions replaces the natural log of fuel treatments, $\log(FT_{it})$, for the inverse hyperbolic sine transform of fuel treatments $asinh(FT_{it})$. The third set of regressions replaces the natural log of fuel treatments, $\log(FT_{it})$, which is calculated using the total acres of fuel treatment within the past 10 years of a fire for natural log of fuel treatments in the past 5 years $\log(FT_{it,5Y})$. The fourth set of regressions replaces an indicator for whether a fire starts in an LSR, LSR_i, with a continuous measure, $AcresLSR_i$, which is the total acres within the 100-acre circle of a fire that falls under LSR status. Standard errors are clustered at the national forest level. First stage F-statistics are calculated via cluster robust-standard errors from the Fixest package in R.

Table S.9: LSR IV - Robustness Checks - Using Different Fixed Effects

	1st Stage	RF Size	RF Cost	IV Size	IV Cost
Ranger District FEs					
LSR_i	-0.156***	0.058	0.072*		
	(0.022)	(0.053)	(0.037)		
$\log(FT_{it})$				-0.371	-0.459*
				(0.343)	(0.253)
1st Stage F-Stat	50.0				
N	9076	9076	9076	9076	9076
Year & Month (of Year) FEs					
LSR_i	-0.133***	0.072	0.115**		
	(0.021)	(0.055)	(0.041)		
$\log(FT_{it})$				-0.545	-0.868**
				(0.431)	(0.388)
1st Stage F-Stat	39.5				
N	9098	9098	9098	9098	9098
State-Year & State-Month FEs					
LSR_i	-0.134***	0.076	0.109**		
	(0.023)	(0.055)	(0.040)		
$\log(FT_{it})$				-0.568	-0.818**
1st Stage F-Stat	32.4				
N	9098	9098	9098	9098	9098
State-Year-Month FEs					
LSR_i	-0.130***	0.090*	0.126***		
	(0.022)	(0.051)	(0.037)		
$\log(FT_{it})$				-0.692	-0.972**
				(0.432)	(0.393)
1st Stage F-Stat	34.5				
N	9098	9098	9098	9098	9098

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The above table explores the robustness of the main IV regression results with the use of different fixed effects. The table reports the results of five separate regressions for the first stage, reduced form, and full IV estimate results using an indicator for whether a fire occurs within a late-successional reserve, LSR_i as an instrument for the natural log of fuel treatments $\log(FT_{it})$. Each regression includes the same sample and controls in Table 3. The first set of regressions replaces National Forest fixed effects for Ranger District fixed effects. The second set of regressions replaces year-month fixed effects with year and month (of year) fixed effects. The third set of regressions replaces year-month fixed effects with state-year and state-month fixed effects. The fourth set of regressions replaces year-month fixed effects with state-year-month fixed effects. Standard errors are clustered at the national-forest level. First stage F-statistics are calculated via cluster robust-standard errors from the Fixest package in R.