Wildfire damages and the cost-effective role of forest fuel treatments

Frederik Strabo[1*], Calvin Bryan[2] and Matthew N. Reimer[1]

[1*]Department of Agricultural and Resource Economics, University of California, Davis, One Shields Ave, Davis, 95715, CA, USA.
[2]Department of Agricultural and Resource Economics, Colorado State University, 301 University Avenue, Fort Collins, 80523, Colorado, USA.

*Corresponding author(s). E-mail(s): ftstrabo@ucdavis.edu; Contributing authors: cal.bryan@colostate.edu; mnreimer@ucdavis.edu;

Abstract

Wildfires have emerged as one of the most pressing environmental challenges of the 21st century, with far-reaching economic and ecological consequences [1]. The buildup of combustible forest fuels is a key contributor to escalating wildfire risk, as decades of suppression policies have allowed fuels to accumulate well beyond historical levels [2]. Although fuel-reduction treatments are central to wildfire risk management [3], they remain underutilized [4], in part due to a limited understanding of their economic benefits [5]. Here, we provide large-scale empirical evidence on the cost-effectiveness of fuel treatments in mitigating wildfire damages. We integrate high-resolution data on wildfires, fuel treatments implemented by the U.S. Forest Service, suppression effort, and economic damages across the Western United States from 2017 to 2023. Using a quasi-experimental design, we find that fuel treatments significantly reduced wildfire spread and severity, avoiding an estimated \$2.7 billion in damages by limiting structure loss, reducing CO_2 emissions, and lowering $PM_{2.5}$ exposure. We estimate each dollar invested in fuel treatments yields \$3.42 in expected benefits. Larger treatments and prescribed burns are especially effective, suggesting that refinements to fuel treatment design could further enhance their impact. Our findings demonstrate the value of investing in fuel treatments and offer actionable insights for optimizing their implementation as wildfire risk intensifies.

Keywords: wildfire mitigation, fuel treatments, forest management, climate adaptation

JEL Classification: H41 , Q23 , Q28 , Q54 , R52

Introduction

Wildfire activity has intensified dramatically in recent decades, leading to widespread economic, environmental, climate, and public health damages [1]. In the United States alone, total annual wildfire-related damages are estimated at \$394–893 billion, equivalent to 2–4% of GDP [6]. These costs stem from property loss, fire suppression, adverse health outcomes, labor disruptions, and degraded ecosystem services [7–12]. Recent estimates suggest that health damages from wildfire-induced $PM_{2.5}$ exposure alone may exceed all other climate-related damages in the United States [13]. Globally, wildfire risk is projected to increase due to climate change, expanding development in the wildland-urban interface, and decades of fire suppression [14–16]. Yet despite mounting damages, key mitigation strategies, such as forest fuel reductions, remain underutilized and lack rigorous evaluation at scale.

The accumulation of combustible material in forests, known as fuel loads, is a primary driver of increasing wildfire severity [2]. Historically, frequent, low-severity fires helped regulate these loads. In California, for example, an estimated 5-12% of the landscape burned annually prior to 1800, much of it through Indigenous cultural burning practices [17]. However, long-standing wildfire suppression policies have disrupted these fire cycles, allowing fuels to accumulate well beyond historical levels, threatening the functionality of forest ecosystems [18, 19].

Fuel-reduction treatments ("fuel treatments"), such as prescribed burns and mechanical biomass removals, have become central to wildfire risk strategies. These treatments aim to reduce fuel loads, maintain open-canopy forest structures, and remove fire-prone species, thereby mimicking natural fire processes [20]. The U.S. Forest Service (USFS) has pledged to treat over 50 million acres—an area roughly the size of Utah—over the next decade through its Wildfire Crisis Strategy, reflecting a shift in federal wildfire policy toward more proactive risk reduction [3].

Despite commitments to accelerate the pace and scale of fuel treatments, they remain underutilized [4], in part because public pressure and risk aversion skew wildfire management resources toward fire suppression rather than prevention [5]. Suppression effort offers immediate and visible results, whereas the benefits of fuel treatments are delayed, uncertain, and difficult to observe. As a result, the value of fuel treatments is often underappreciated by the public and policymakers, leading to persistent barriers in their broader implementation, including regulatory, funding, and capacity constraints. These dynamics reflect a classic public goods problem: despite their broad societal benefits, there are insufficient incentives to invest in prevention measures without clear, credible evidence of their benefits.

Demonstrating the benefits of fuel treatments, however, has proven difficult due to data limitations and the complexity of attributing reductions in wildfire spread, severity, and damages to fuel treatments. Until recently, comprehensive records on fuel treatment locations, wildfire perimeters, suppression effort, and damages were scarce or fragmented. Furthermore, wildfire behavior is shaped by the interaction of fuels, weather, topography, and suppression effort, making causal identification challenging. Consequently, prior studies rely on model-based fire simulations or localized case studies that are difficult to generalize and often assess hypothetical treatment scenarios rather than real-world implementations [21–23]. As a result, they offer limited insights into whether current treatments are cost-effective or under which conditions they deliver the greatest benefits.

We present large-scale empirical evidence on the effectiveness of fuel treatments in mitigating the spread, severity, and damages of wildfires. Our analysis integrates high-resolution data on wildfire perimeters, fuel treatment locations, suppression effort, fire simulation outputs, key determinants of fire behavior, and wildfire damages, spanning 285 wildfires that intersected with USFS fuel treatments across 11 western U.S. states from 2017 to 2023 (Fig. 1a). We focus on three of the primary contributors to wildfire damages—structure loss, CO_2 emissions, and $PM_{2.5}$ exposure, representing economic, climate change, and public health impacts and accounting for an estimated \$185–540 billion in annual damages [6]. By monetizing the benefits of fuel treatments and identifying the characteristics that enhance their effectiveness, we aim to inform public policy and investment decisions for proactive wildfire risk mitigation.

Wildfires and Fuel Treatments in the Western U.S.

Wildfire has long shaped forest ecosystems in the Western U.S. For millennia, lightning ignitions and Indigenous burning practices maintained a fire regime of frequent, low-severity fires in much of the forest landscape, clearing excess vegetation and supporting ecological resilience. This regime was disrupted in the early 20th Century when the newly established USFS—tasked with overseeing many of the region's most fire-prone landscapes—institutionalized wildfire suppression as a central management goal. Most notably, the 1935 "10 a.m. policy" aimed to extinguish all fires by the morning after ignition [26]. In the decades that followed, federal, state, and local agencies adopted similar approaches [27], effectively minimizing fire in the short term while creating long-term ecological and economic risks by allowing vegetative fuels to accumulate.

In response to the ecological risks created by a century of fire suppression, public land agencies have increasingly adopted fuel treatments to restore natural fire regimes and reduce wildfire risk. By reducing excess fuels and modifying forest structure, these treatments aim to lower burn severity and sustain critical ecosystem services such as improved air and water quality, nutrient cycling, post-fire carbon storage, and biodiversity [28–32]. In practice, their placement often prioritizes the protection of homes, communities, and critical infrastructure—particularly in the wildland–urban interface [33]. Because they are designed to protect assets at risk, fuel treatments are frequently located in areas where suppression efforts are most likely to be deployed, allowing them to serve a dual role: modifying fire behavior and improving the effectiveness of firefighting operations.

Yet despite their ecological and operational benefits, fuel treatments remain underutilized relative to suppression, reflecting deeper institutional dynamics and economic incentives [5]. The political costs of allowing a fire to burn are immediate and visible, while the benefits of preventive measures like fuel treatments are delayed and uncertain. As the saying goes, a "fire put out is a fire put off." These incentives have led to considerably more resources directed towards wildfire suppression than prevention, with USFS expenditures on suppression exceeding fuel treatment spending by nearly tenfold (Fig. 1c,e).

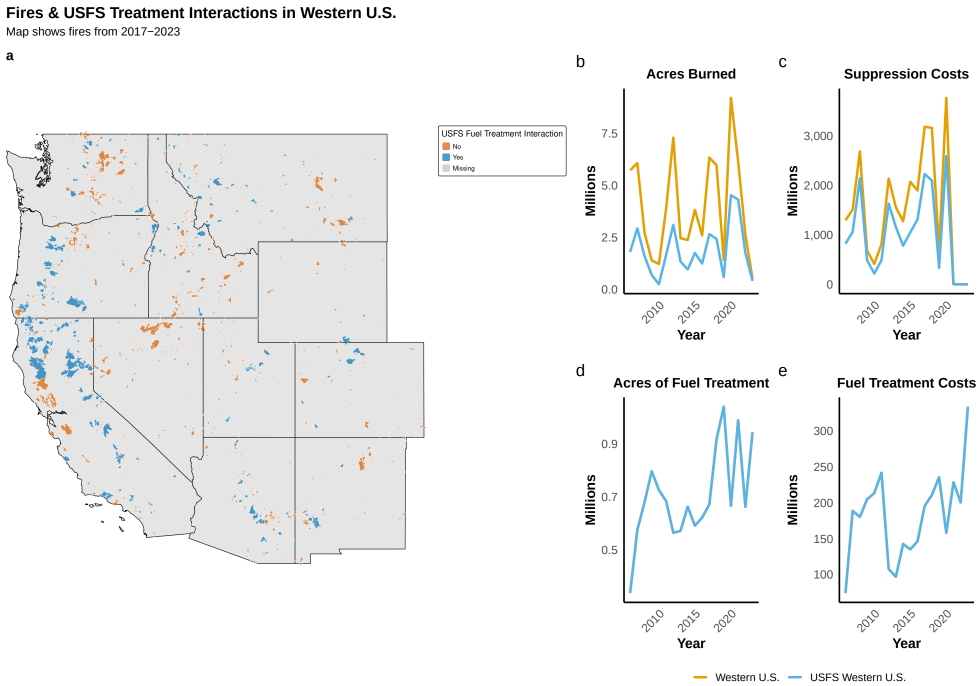

Fig. 1: **Wildfires and fuel treatments in the Western U.S. a**, Perimeters of all large wildfires (>1,000 acres) igniting in the western U.S. between 2017 and 2023. Blue fires ($N = 285$) intersect with USFS fuel treatments and comprise our estimation sample. Orange fires ($N = 1{,}600$) do not intersect with USFS fuel treatments. **b-e**, Annual acres burned (millions), suppression costs (millions, 2023 USD), footprint acres of fuel treatment (millions), and fuel treatment costs (millions, 2023 USD) for the entire Western U.S. (orange) and USFS lands in the Western U.S. (blue). Footprint acres represent the total unique area treated at least once within the year, regardless of frequency. Suppression costs reflect only reported expenditures from incidents tracked in the ICS-209 system and are available through 2020. Other outcomes extend through 2023.

These institutional dynamics are compounded by operational constraints within the USFS, which manages the majority of forestland in the Western U.S. and accounts for most suppression costs and burned acreage (Fig. 1b,c). With just 30,000 employees overseeing 193 million acres, it is difficult for the agency to scale up fuel treatment projects, which are often labor-intensive, logistically complex, and face a variety of administrative constraints [34]. As a result, more acres burn each year than are treated (Fig. 1b,d). While fuel treatments do intersect with many wildfires (Fig. 1a), the persistent imbalance between treatment and suppression highlights a reactive posture—one we evaluate through the lens of cost-effectiveness.

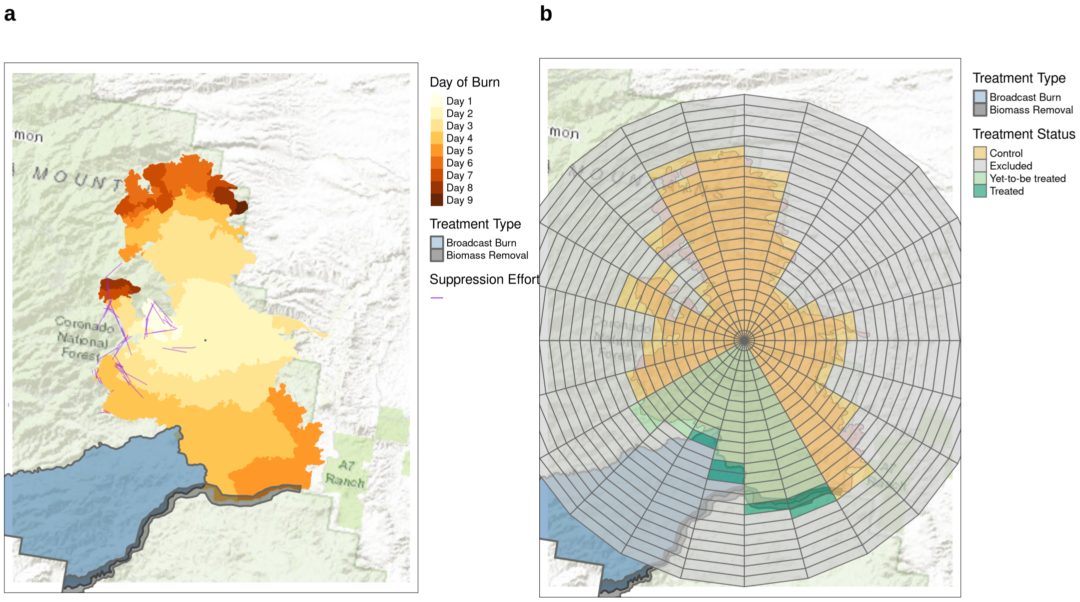

Fig. 2: **Estimating the impact of fuel treatments. a**, Daily progression of the 2017 Burro Fire in Arizona. The day and area burned are depicted in red (shaded from white-dark red). The Burro Fire intersected with two fuel treatments: a broadcast burn (blue) and biomass removal (black). Fire suppression effort (containment lines and aerial retardant drops) is shown in purple, indicating where firefighting resources were deployed to halt fire spread. **b**, To illustrate our research design, the Burro Fire is divided into spatial cells—or "plots"—that have a unique direction and distance from the ignition point [24]. A direction is considered "treated" (green) if it intersects with at least one fuel treatment. Directions that do not intersect any fuel treatments (gold) serve as controls. Plots are further classified as "yet-to-be treated" (light green), "treated" (dark green), and "control" (gold). Excluded plots are shown in gray. Yet-to-be-treated and control plots are used to estimate what fire spread and burn severity would have been in the treated plots if they had not intersected with a fuel treatment, following the imputation method of Borusyak et al. [25].

Estimating the Effect of Fuel Treatments on Wildfires

We estimate the effects of fuel treatments on wildfire spread and severity, controlling for a range of factors that shape wildfire behavior. We examine how treatments vary by treatment type, size, time since implementation, and proximity to suppression effort to identify conditions under which treatments are most effective. Using our estimated treatment effects, we predict counterfactual wildfire behavior in the absence of any fuel treatments to quantify avoided damages from structure loss, CO_2 emissions, and

$PM_{2.5}$ exposure. Comparing these benefits to the costs of implementing treatments, we assess whether fuel treatments are a cost-effective wildfire mitigation strategy.

Interpreting an empirical relationship between fuel treatments and wildfire behavior as causal is challenging due to the non-random allocation of treatments and suppression effort, creating the potential for selection bias. Both fuel treatments and fire suppression resources are allocated to protect areas of elevated wildfire risk, where fires are more likely to spread or threaten valuable assets [8, 24, 35–37]. Moreover, suppression resources are often deployed in ways that respond to the presence of nearby fuel treatments [38]. As a result, simple comparisons of wildfire behavior between treated and untreated areas are likely to be confounded by systematic differences in underlying fire risk and fire management.

We address these challenges using a spatial difference-in-differences research design that exploits the quasi-random nature of wildfire ignition and directional spread. The precise location of ignition points is largely unpredictable, meaning the direction and distance at which a fire encounters a fuel treatment is likely to be independent of factors that also influence fire behavior. For each fire, we compare changes in fire behavior in directions that encounter treatments to those that do not, before and after the fire reaches a treatment, controlling for predictable fire spread patterns from fire simulation outputs, weather, and suppression effort (Fig. 2). A key strength of this design is that it naturally controls for unobserved factors that influence where treatments are typically placed—often near assets or in high-risk areas—by comparing a fire's behavior along the same path before and after treatment, net of common distance-related trends across fires. Under the assumption of "parallel trends"—that, in the absence of treatment, fire behavior would have evolved similarly in treated and untreated directions—our approach yields credible estimates of the causal effect of fuel treatments on wildfire spread and severity. Consistent with this assumption, we find no evidence that fire behavior evolves differently between treated and untreated directions before encountering a fuel treatment (Fig. 3a,b, left of the dashed line).

Fuel Treatments Reduce Fire Spread & Severity

We estimate the impact of fuel treatments on the probability of fire spreading to an adjacent plot and the burn severity of a plot, conditional on the plot burning (Figure 3a-b, right of the dashed line). The likelihood of a fire spreading declines by 13.5 percentage points, on average, immediately after encountering a fuel treatment; however, the effect dissipates with distance, shrinking to 9.6 percentage points at 1.5 km and becoming negligible by 2.5 km. In contrast, burn severity exhibits an immediate and sustained reduction of 7.5–10.7% over the same distance. This difference reflects the nature of fire behavior: while fire spread is immediately influenced by a discontinuity in forest fuels—either halting or redirecting the fire's path—burn severity depends on the overall reduction in surface and canopy fuels, which can moderate fire intensity even after the fire passes beyond the initial treatment boundary [39, 40].

Our findings are robust across a range of alternative specifications and sensitivity analyses (Supplementary Tables S5—S11). In particular, a matching-based approach that improves the comparability of treated and untreated plots based on observable characteristics yields similar and more significant reductions in fire spread and severity (Extended Data Fig. 1), demonstrating that our results do not simply reflect pre-existing differences between plots. To further test the validity of our spatial difference-in-differences design, we conduct a placebo test using plots with planned-but-not-implemented fuel treatments. These projects were selected for treatment but never completed, allowing us to assess whether fire spread patterns shift discontinuously at the boundaries of areas selected for treatment, even in the absence of actual fuel reductions. We find no evidence of an effect on fire spread in these placebo plots (Extended Data Fig. 2), further supporting the credibility of the parallel trends assumption. However, we do observe slightly elevated burn severity in these plots, consistent with treatments being targeted to high-risk areas. As a result, our estimates may understate fire severity in the absence of fuel treatments, indicating that our estimates likely represent conservative lower bounds.

We also quantify the cumulative effects of fuel treatments on fire spread and severity using a survival analysis framework, reflecting the fact that preventing fire spread at one location decreases the likelihood of continued spread beyond it. We estimate these effects using the unconditional probability of burning, defined as the product of the probability that fire reaches a plot and the probability that the plot burns if reached. We track how this unconditional probability declines with distance from the point where a fire first encounters a fuel treatment. Treated directions are estimated to be 12.1 percentage points less likely to continue burning beyond 2.5 km than if they had not encountered a fuel treatment (Fig. 4a & Extended Data Fig. 3a), corresponding to a 36% reduction in total burned area. Burn severity also declines over the same distance, with treated plots experiencing 20–30% lower severity than if they had not been treated (Fig. 4b & Extended Data Fig. 3b), equivalent to a 26% reduction in moderate-to high-severity fire.

The Determinants of Fuel Treatment Effectiveness

Fire progression maps reveal substantial heterogeneity in the effectiveness of fuel treatments in halting wildfire spread (Extended Data Fig. 4). We examine four factors that may explain this heterogeneity: treatment type, time since treatment implementation, treatment size, and proximity to suppression resources.

Previous research in fire ecology has shown that treatments are most effective when recently completed and when mechanical thinning is combined with prescribed burning [41]. Our results reinforce the importance of treatment type: treatments that include prescribed fire—either alone or alongside mechanical thinning—are significantly more effective than mechanical-only treatments (Fig. 5c). These effects are especially pronounced immediately after encountering a fuel treatment, indicating that prescribed fire enhances the short-term effectiveness of treatments in halting fire spread. We also find that larger treatments lead to greater reductions in fire spread and burn severity (Fig. 5b and Extended Data Fig. 6), which may be due to their having more interior area relative to their boundary, thereby reducing exposure to surrounding fuels and making them more effective at disrupting fuel continuity and slowing fire progression [42–44]. In contrast, we find limited evidence that time since treatment

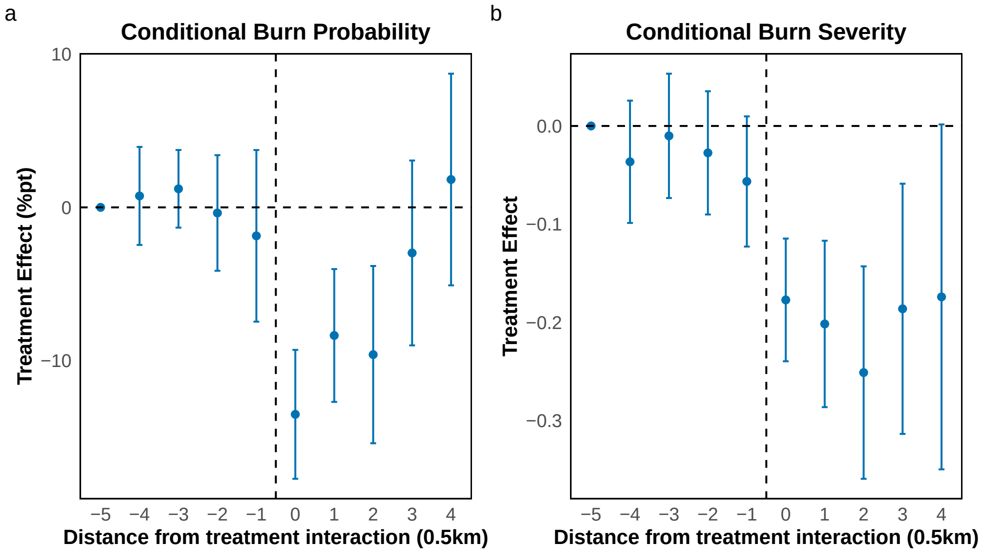

Fig. 3: **Conditional effects of fuel treatments on fire spread and burn severity. a-b**, Estimated average effects of fuel treatments on **(a)** the probability of a fire spreading, conditional on reaching a plot, and **(b)** burn severity, conditional on burning, within 2.5 km of a fire's initial interaction with a fuel treatment. Pre-treatment effects (left of the dashed line) are measured relative to 2.5 km before the fuel treatment (distance bin -5). Post-treatment effects (right of the dashed line) are estimated using imputation following the method of Borusyak et al. [25]. Error bars represent 95% confidence intervals, clustering at the fire level.

significantly affects fire spread within a 10-year window (Fig. 5d), though it does influence conditional burn severity (Extended Data Fig. 5).

Fuel treatments are substantially more effective at reducing wildfire spread when supplemented with suppression resources. We estimate that plots receiving suppression effort are 11-22 percentage points less likely to experience fire spread up to 2 km after encountering a fuel treatment than they would have without fuel treatments (Fig. 5a). In contrast, fuel treatments without suppression effort are effective at reducing fire spread only within 0.5 km, with an estimated six percentage point reduction relative to no treatment. Importantly, these effects cannot be explained solely by suppression effort being strategically placed in areas close to fuel treatments: we find similarly large reductions in fire spread even when comparing plots with both fuel treatments and suppression effort to those with suppression effort alone (Table S7). This finding supports the idea that fuel treatments enhance suppression effectiveness by reducing flame lengths and the rate of heat release along the fire perimeter, thereby making it easier for firefighters to contain fire spread [45, 46]. In contrast, we find that suppression resources do not significantly reduce conditional burn severity relative to treated areas without suppression (Extended Data Fig. 5).

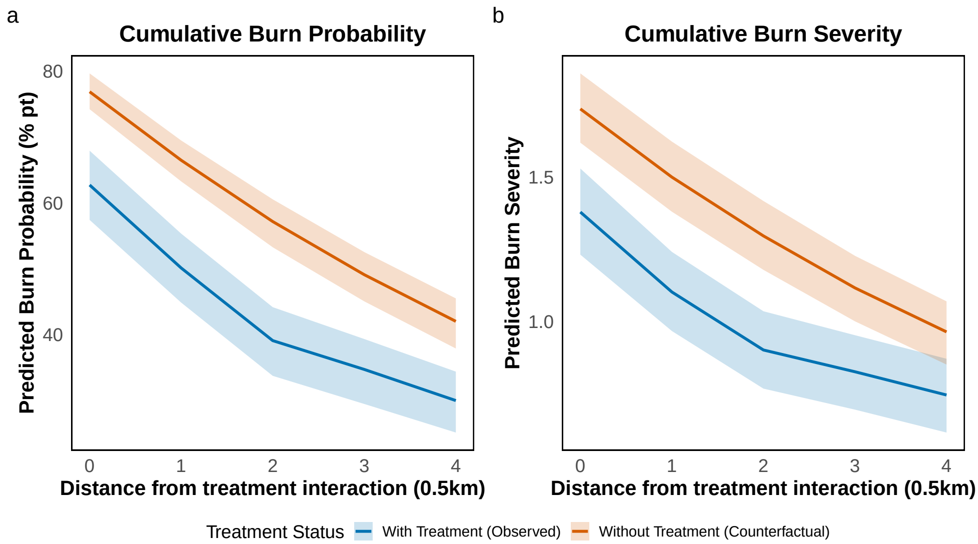

Fig. 4: **Cumulative effect of fuel treatments on fire spread and burn severity. a-b**, Estimated average unconditional **(a)** probability of burning and **(b)** burn severity for all treated directions 2.5 km after a fire's initial interaction with a fuel treatment. "With treatment" outcomes (blue) represent the observed average burn probability and severity. "Without treatment" outcomes (orange) represent the estimated counterfactual of what burn probability and severity would have been in the absence of a fuel treatment. 95% confidence intervals are based on 1,000 bootstrap simulations, resampling fires with replacement.

The Economic Benefits of Fuel Treatments

We estimate the economic benefits of fuel treatments by comparing observed wildfire spread and damages from 2017-2023 to a counterfactual scenario in which there were no USFS fuel treatments to limit fire progression. We predict fire spread in the absence of fuel treatments for areas that were, in fact, treated. This comparison reveals that fuel treatments reduced total burned area by 151,231 acres—equivalent to a 36% reduction (Table 1).

To quantify economic benefits, we focus on two primary outcomes: saved structures and avoided emissions. Using high-resolution data on structures, we estimate that fuel treatments prevented the loss of 3,859 buildings. Assuming emissions are proportional to acres burned, we estimate that fuel treatments avoided 2.75 million tons of CO_2 and 26,075 tons of $PM_{2.5}$. Combining estimates of fire-level $PM_{2.5}$ exposure and mortality risk from the literature [11, 47], we estimate that 28 premature deaths were averted. Monetizing these impacts yields $833 million from avoided structure loss, $500 million from reduced CO_2 emissions, and $1.4 billion from avoided $PM_{2.5}$-related mortality and productivity losses. Dividing these benefits by the cost

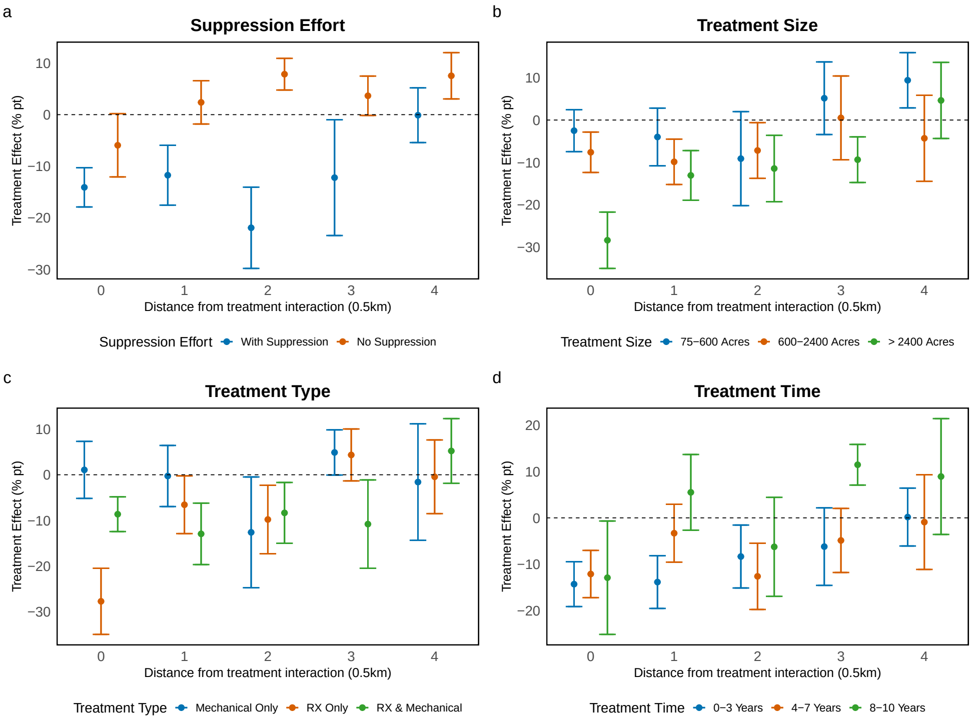

Fig. 5: **Heterogeneous treatment effects of fuel treatments on the probability of fire spread. a-d,** Estimated average treatment effects of fuel treatments on the probability of a fire spreading, conditional on reaching a plot, by: **(a)** suppression resources (with or without), **(b)** treatment size (small, medium, or large), **(c)** treatment type (mechanical thinning, prescribed burn, or both), and **(d)** time since treatment (short, medium, or long) within 2.5 km of the initial treatment-fire interaction. Estimated treatment effects are generated by estimating our spatial difference-in-differences model on subsamples defined by each source of heterogeneity, retaining only treated observations within each category while using the full set of never-treated observations as controls. Error bars represent 95% confidence intervals, clustering at the fire level. Estimates in **(a)** are generated using a subsample of 178 fires for which we have full fire suppression effort data. Treatment effects are estimated using the method of Borusyak et al. [25].

of implementing treatments yields a benefit-cost ratio of $39.35 for treatments that intersected with wildfires (Table 1).

While this benefit-cost ratio is substantial, it only captures the realized benefits of treatments that intersected with fires and does not reflect the uncertainty in land managers' decision-making when siting treatments without knowing when and where future fires will occur. To evaluate cost-effectiveness under this uncertainty, we calculate an "ex-ante" benefit-cost ratio that accounts for all fuel treatments conducted by the USFS, considering both the likelihood that a treatment intersects with a fire during its effective lifetime and how this likelihood varies across fuel treatment sizes.

Consistent with prior work [48], we find that larger fuel treatments are more likely to intersect with a fire over a 10-year horizon (Extended Data Fig. 7): 70.4% for large treatments (>2,400 acres), compared to 38.5% and 25.4% for medium (600–2,400 acres) and small treatments (75–600 acres), respectively. Larger treatments also deliver greater benefits: $9.2 million for large, $3.7 million for medium, and $818,000 for small treatments, on average. Combining these size-specific benefits with their respective probabilities of fire interaction and dividing by their implementation costs yields expected benefit-cost ratios of $4.88 for large, $3.21 for medium, and $2.69 for small fuel treatments (Table 1).

Aggregating across all USFS fuel treatments that could have intersected with wildfires between 2017 and 2023, we estimate an overall ex-ante benefit-cost ratio of $3.42, suggesting that each dollar invested in fuel treatments yields over three dollars in expected avoided damages (Table 1). The median ex-ante benefit-cost ratio is even higher ($8.26), indicating that while most projects are cost-effective, a small number of low-performing treatments skew the distribution—highlighting the potential for improved targeting and design.

Table 1: Counterfactual Benefits of USFS Fuel Treatments

A. Physical Savings

Acres Burned	Structures Lost	CO_2 Emissions (t)	$PM_{2.5}$ Emissions (t)	Deaths
151,231	3,859	2,749,051	26,075	28

B. Economic Costs & Savings

Treatment Cost	Housing Values	Social Cost of Carbon	Health & Labor	C-BCR
$69,829,517	$833,009,806	$508,574,362	$1,406,529,722	$39.35

C. Ex-Ante Benefit-Cost Ratios

Small (75-600)	Medium (600-2400)	Large (> 2400)	Total	Median
2.69	3.21	4.88	3.42	8.26

A. Estimated physical savings from fuel treatments interacting with wildfires in our sample. **B.** Economic costs (i.e., expenditures) and estimated savings from fuel treatments. C-BCR denotes the benefit-cost ratio conditional on fuel treatments interacting with a fire. **C.** Predicted ex-ante benefit-cost ratios for all U.S. Forest Service treatments conducted from 2007–2023 in the Western U.S., categorized by treatment size.

Discussion

A century of wildfire suppression policies has disrupted fire-adapted forest ecosystems, allowing fuel loads to accumulate, driving larger, more severe, and costlier wildfires. Our findings demonstrate that fuel-reduction treatments are a cost-effective strategy to mitigate these impacts. We estimate that fuel treatments interacting with wildfires between 2017 and 2023 significantly decreased wildfire spread and severity, resulting in avoided damages from structure loss, CO_2 emissions, and $PM_{2.5}$-related health impacts totalling over $2.7 billion. On average, fuel treatments are expected to generate $3.42 in benefits for every dollar invested, demonstrating that they are not only ecologically beneficial but also economically justified.

Despite their cost-effectiveness, opportunities to improve the design and targeting of fuel treatments remain. We find that treatments involving prescribed fire are especially effective at disrupting fire spread, which is consistent with findings in the fire ecology literature that prescribed burns create more continuous fuel breaks by reducing surface and fine fuels that mechanical thinning often leaves behind [41]. We also provide evidence that larger treatments are not only more effective at limiting wildfire spread but also more cost-effective at reducing damages. This finding reinforces recent policy debates that advocate for consolidating fuel-treated areas into fewer, larger, and more strategically located treatments [49]. These insights are made possible by our large-scale empirical framework, which evaluates how treatments influence wildfire spread at the landscape scale, capturing spatial dynamics that localized studies often cannot [50].

Our findings lend support to U.S. federal and state agencies that have committed to accelerating the pace and scale of fuel-reduction treatments. However, land managers face a litany of legal and regulatory barriers to implementing large-scale treatments, including environmental review requirements under the National Environmental Policy Act (NEPA) or species protections under the Endangered Species Act (ESA) [51]. These constraints underscore the need to consider policy reforms that enable more proactive landscape-scale interventions [34, 52]. The significant divergence between the overall and median benefit-cost ratios (Table 1) further emphasizes the importance of targeting treatments effectively to maximize returns. By providing a data-driven framework and open-source tools, our study offers practical guidance for evaluating the cost-effectiveness of fuel treatments, which can be readily applied across different states and regions. Identifying which treatments are most likely to yield high returns can support more strategic, evidence-based decision making—a need made more urgent by recent federal budget cuts and escalating wildfire risks.

Our estimated benefit-cost ratio of 3.42 is broadly consistent with, though somewhat more conservative than, those reported in prior literature. For instance, a recent meta-analysis finds an average benefit-cost ratio of 7.04 across 16 studies encompassing a wide range of benefits [23]. Unlike our empirical approach, however, these studies are largely simulation-based and often model scenarios involving hypothetical, large-scale implementation of fuel treatments, in terms of both the total area treated and the size of individual projects. In contrast, our study evaluates the effectiveness of real-world fuel treatment projects implemented by the USFS, which are generally smaller in scale, more fragmented, and subject to operational and institutional constraints.

Moreover, our benefit-cost ratio also explicitly incorporates the uncertainty that a treated area will intersect with a fire—a factor not always addressed or realistically modeled in prior studies. These distinctions reinforce the policy relevance of our findings, suggesting that returns to fuel treatments could increase if their implementation were scaled and coordinated more effectively.

Our analysis also omits several important pathways through which treatments may provide additional benefits. For example, we do not assess the role of treatments in reducing the likelihood of ignition or deterring small fires from becoming large and destructive—a mechanism shown to substantially lower suppression costs [38]. Nor do we account for a broader suite of economic, ecological, and social benefits, including avoided suppression costs, improved water supply and quality, revenues from thinning operations, local job creation, and the non-use value of restored ecosystems, among others [53–56]. In addition, our analysis is limited to USFS treatments and does not evaluate the effectiveness of fuel treatments on private lands or by other public agencies, which may differ in their approaches and effectiveness in mitigating wildfire risks. Future research that incorporates these additional benefit streams and land ownership types will be essential to fully assess the economic and ecological value of fuel management strategies.

While our estimate of fuel treatment benefits is likely conservative, the associated cost estimates may also be understated. For example, we do not consider additional costs from prescribed burns, such as $PM_{2.5}$ or CO_2 emissions, nor do we account for foregone carbon sequestration resulting from the removal of forest fuel biomass. Both could represent meaningful components of the full social cost of implementing fuel treatments, although evidence suggests that prescribed burns typically emit far less than the wildfires they help prevent [57]. A full accounting of emissions, sequestration, and other ecosystem service tradeoffs would require detailed modeling that is beyond the scope of this study. Incorporating these dynamics is an important direction for future research to better quantify the net social returns to fuel treatment investments.

Our analysis also abstracts from dynamic interactions between fuel treatments and fire suppression strategies. While we find that fuel treatments are especially effective when complemented with suppression effort, we do not provide insight into how suppression resources are allocated within fires or whether such allocations would differ in the absence of fuel treatments. Our benefit-cost analysis implicitly assumes that suppression effort would not have been deployed differently in the absence of treatments—a simplification that warrants further investigation. Previous work suggests that the presence of nearby fuel treatments may reduce the need for costly suppression resources, freeing up limited resources to be allocated elsewhere [38]. Yet little is known about how this tradeoff plays out in real-time within a fire [58]. Future research is needed to explore how suppression resources and fuel treatment placement can be jointly optimized to maximize the impact of scarce wildfire management resources.

Despite the clear economic rationale for fuel treatments, capacity and funding constraints pose a significant challenge to scaling them up. These constraints are compounded by land managers' incentives to prioritize short-term fire suppression effort over long-term preventive treatments, as immediate fire response helps avoid public backlash and lawsuits, while the benefits of prevention may not be immediately visible.

Importantly, fuel treatments also exhibit the characteristics of a public good: many of their benefits, particularly from reduced smoke exposure, extend beyond the jurisdiction or landowner that implements them [59]. This geographic mismatch between who pays and who benefits can discourage local investment and create incentives for private landowners to free-ride on publicly funded mitigation. Addressing these challenges will require innovative policy solutions, such as targeted subsidies, creative funding mechanisms, and public-private partnerships, that both align incentives across jurisdictions and alleviate capacity and funding constraints, unlocking more effective and widespread fuel treatment projects on both public and private lands.

In sum, our results provide compelling evidence that fuel treatments are a cost-effective strategy for forest restoration and wildfire mitigation, offering a promising pathway to address one of the most urgent and costly environmental challenges of the 21st century. Yet realizing their full potential will require more than scientific consensus—it will demand bold policy reform. Thoughtful consideration of environmental policy reform, coupled with targeted economic incentives, will be essential to overcoming the barriers that limit effective fuel treatment implementation at scale.

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Methods

Our empirical approach integrates wildfire perimeters, economic damages, fuel treatments implemented by the U.S. Forest Service, and suppression activities across eleven western U.S. states (Fig. 1a) to examine how fuel treatments influence wildfire spread, severity, and damages. Below, we outline our dataset construction, quasi-experimental design, counterfactual simulations, and benefit-cost calculations. Data sources and detailed variable descriptions are detailed in Supplementary Tables S1 and S2.

Overview

Our research design relies on variation in the direction a fire spreads and the distance at which it intersects with a fuel treatment. To illustrate, consider the 2017 Burro Fire depicted in Fig. 2. We divide each fire's area into spatial cells ("plots") defined by their unique direction and distance from ignition, following Plantinga et al. [24]. The landscape is partitioned into 24 radial directions and 0.5 km distance intervals from ignition to perimeter. A direction is "treated" if any plot along it intersects a fuel treatment; otherwise, it serves as a control. Within treated directions, plots before the first treatment are classified as "yet-to-be-treated," while those at or beyond it are "treated." We use yet-to-be-treated and control plots to estimate how fires would have behaved in treated plots absent fuel treatments.

Data

We assemble information on fire perimeters, ignition characteristics, and burn severity for large fires igniting on USFS land taken from the Monitoring Trends in Burn Severity (MTBS) database (perimeters are only available for fires greater than 1,000 acres in the Western U.S.). Our analysis focuses on the 2017–2023 period, for which comprehensive data on fire suppression activities are available.

Daily fire progression is obtained from NASA satellite data [60], and ignition points are imputed as the centroid of first-day burn polygons. Plots are classified as burned if their centroid intersects a fire perimeter, with burn severity measured on a 1 ("Very Low") to 4 ("High") scale. A plot is classified as "treated" if at least 50% of its area intersects a fuel treatment; results are robust to alternative thresholds (Supplementary Table S10).

Data on fuel treatment locations, timing, and costs are obtained from the USFS Hazardous Fuel Treatment Reduction database (FACTS). We focus on completed treatment projects between 2007 and 2023, allowing a fire to intersect with fuel treatments that were completed ten years before its ignition. We choose ten years as the cutoff for counting fuel treatments, as previous studies have shown that fuel treatment effectiveness is diminished after 9–14 years [61, 62]. Treatment size is defined as the total footprint area of all spatial activities associated with a project [63]. We exclude treatments with cost-per-acre values that exceed ten standard deviations above the mean to address concerns of measurement error and outliers in FACTS [64]. As a robustness check, we also estimate treatment costs using an alternative approach based on USFS budget justifications and find a similar benefit-cost ratio (discussed in more detail below). Our final sample includes 285 wildfires between 2017 and 2023 that intersect with at least one fuel treatment completed prior to ignition, representing 14,760,206 acres burned, or 45.7% of all acres burned by MTBS fires in the Western U.S. during this time period.

We assign a comprehensive set of covariates to each plot, including proximity to fire suppression effort (location of large airtanker drops—sourced from USFS—and fire suppression lines—sourced from the National Interagency Fire Center), topographic characteristics (elevation, slope, aspect, and the topographic ruggedness index—derived from LANDFIRE), weather conditions (wind speed, direction, short- and long-term drought indicators—obtained from GridMET and measured based on the date of burning), economic and infrastructural factors (distance to the nearest wildland-urban interface (WUI) Census Block, USFS roads, and U.S. highways [65, 66]), and indicators for whether a plot lies within the WUI, a USFS National Forest, or a designated wilderness area.

To control for predictable fire spread patterns, we generate fire simulation outputs from the FlamMap Minimum Travel Time (MTT) fire spread model [67]. We simulate fire behavior using wind speed and direction at the time and location of ignition, pre-treatment vegetation characteristics from LANDFIRE 2001, and standardized initial fuel moisture conditions. Model outputs include fire arrival time and fireline intensity. We conducted simulations at a 150-meter resolution for computational feasibility and calculated each plot's average change in arrival time and fireline intensity following Plantinga et al. [24]. More details are provided in the Supplementary Appendix.

To estimate wildfire damages, we obtain structure data from the "Wildfire Risk to Communities" dataset, which reports housing and structure counts at a 30-meter resolution as of 2020 [68]. We draw estimates of CO_2 and $PM_{2.5}$ emissions from the "Wildland Fire Emissions Inventory System" (WFEIS), which provides aggregate emissions by fire, and population- and day-weighted estimates of $PM_{2.5}$ smoke exposure from Wen et al. [59] for fires occurring between 2017 and 2020. Because comparable exposure estimates are unavailable for fires from 2021 to 2023, we impute population-day $PM_{2.5}$ exposure for these fires based on their total $PM_{2.5}$ emissions. Total emitted $PM_{2.5}$ is a strong predictor of smoke exposure ($R^2 = 0.58$; Supplementary Fig. S.2), allowing us to extend our exposure and damage estimates for fires from 2021 to 2023.

Empirical Strategy

We estimate how fuel treatments influence wildfire spread and severity to predict economic damages avoided by their implementation. This requires estimating how wildfires would have behaved in treated plots absent treatment, using untreated (yet-to-be-treated and control) plots as counterfactuals. Since treatments are often placed where fires are more likely to spread or threaten assets, this strategy must address systematic differences between treated and untreated areas.

We address these challenges by exploiting quasi-random variation in fire ignition locations relative to pre-existing fuel treatments. While landscape features influence ignition risk, their precise location is unpredictable, generating exogenous variation in which directions receive treatment and the distance at which a fire first encounters a treated area. This variation allows us to compare wildfire behavior across treated and untreated directions within fires, controlling for unobserved fire-direction-specific factors and systematic distance-related trends across fires, thereby isolating the causal effect of fuel treatments.

Estimating treatment effects

We estimate treatment effects using a conditional hazard framework adapted from Plantinga et al. [24]. Our analysis focuses on the active spread of fires, using only those plots that were reached by a fire's spread. For burn severity, we further restrict the sample to burned plots only; hence, our estimates can be interpreted as the effect of fuel treatments on fire severity, conditional on burning.

Let Y_{fld} denote wildfire outcome in fire f, direction l, and distance bin d from its origin. Under the parallel trends assumption that, absent treatment, fire behavior would have evolved similarly in treated and untreated directions, we can write Y_{fld} as

$$Y_{fld} = \alpha_{fl} + \eta_d + X'_{fld}\Gamma + \theta_{fld} \cdot D_{fld} + \epsilon_{fld}, \tag{1}$$

where X_{fld} denotes a vector of plot-specific observable characteristics, ϵ_{fld} denotes the unobservable idiosyncratic component of fire behavior, and D_{fld} denotes a binary variable equal to one if a plot is treated. Fire-direction fixed effects, α_{fl}, control for unobserved factors that are constant within a direction, such as assets at risk, prevailing fire spread patterns, and persistent landscape features, while distance fixed effects, η_d, capture unobserved systematic changes in a fire as it spreads outward from the ignition point. To avoid complications that arise from multiple treatments [69], we drop all plots in treated directions that spread beyond a treated area.

When modeling fire spread, we define Y_{fld} as a binary variable equal to one if a plot burned. The linear probability model in Eq. 1 is then analogous to a linear approximation of a discrete-time conditional hazard function, where distance fixed effects η_d capture the baseline hazard at distance d. When modeling burn severity, we define Y_{fld} as average burn severity. In both cases, θ_{fld} represents the plot-specific treatment effect, conditional on the fire not yet being extinguished (spread) or the plot burning (severity).

We apply the imputation method of Borusyak et al. [25], estimating α_{fl}, η_d, and Γ in Eq. 1 using only untreated (control and yet-to-be-treated) plots. These estimates are then used to predict counterfactual outcomes in the absence of treatment, $\hat{Y}^0_{fld}$, for treated plots. Plot-specific treatment effects are then calculated as the difference between observed and counterfactual outcomes: $\hat{\theta}_{fld} = Y_{fld} - \hat{Y}^0_{fld}$. We weight regressions by plot acreage to adjust for varying plot sizes, and estimate clustered standard errors at the fire level to account for spatial autocorrelation.

We compute the average treatment effect for treated plots that are h distance bins from the first fuel treatment interaction. Let δ_{fl} denote where fire f and treated direction l first intersects a treatment, and define $K_{fld} = d - \delta_{fl}$. The average effect at distance h is $\tau_h = \sum_{fld} \mathbf{1}[K_{fld} = h]\theta_{fld}/N_h$, where N_h denotes the number of plots for which $K_{fld} = h$. These dynamic treatment effects are shown in Fig. 3a,b.

We choose the estimator proposed by Borusyak et al. [25] because it addresses the biases arising from differential timing (i.e., directions interact with treatments at different distances) and heterogeneous treatment effects that can distort conventional two-way fixed effects models. Further, its imputation-based approach allows us to estimate plot-specific treatment effects, facilitating the analysis of treatment effect heterogeneity and the prediction of counterfactual fire behavior in the absence of fuel treatments. We also apply alternative methods commonly used in the literature [70, 71] and find similar results (Supplementary Table S6).

Investigating parallel trends

We assess the parallel trends assumption by estimating a version of Eq. 1 with indicators for distances before treatment interaction:

$$Y_{fld} = \alpha_{fl} + \eta_d + X'_{fld}\Gamma + \sum_{h=-1}^{\underline{h}+1} \tau_h \mathbf{1}[K_{fld} = h] + \epsilon_{fld}. \tag{2}$$

Pre-treatment effects, τ_h, represent differential trends in outcomes between treated and control directions prior to treatment, relative to a baseline ($\underline{h} = -6$). Rejecting the null hypothesis $H_o : \tau_h = 0 \;\forall\; h \leq -1$ would be evidence against the parallel trends assumption. We estimate Eq. 2 using only control and yet-to-be-treated plots, thereby avoiding bias from post-treatment effects contaminating estimates of pre-treatment effects [25, 72].

Challenges for causal identification

Although fire ignition locations vary quasi-randomly, violations of the parallel trends assumption remain possible. Fuel treatments are strategically located in areas where fires are more likely to spread and burn, which may cause treated and untreated directions to become increasingly dissimilar as fires advance toward treatments. This systematic placement implies that, without fuel treatments, fires in treated directions could exhibit more severe behavior than those in untreated directions.

Treated directions may also exhibit differential trends in fire behavior due to sample selection. We restrict our sample to only those fires that intersect with a fuel treatment, excluding fires in which treated directions were extinguished before reaching a treatment. As a result, treated directions in our sample are mechanically more likely to have burned than control directions, particularly at greater distances from ignition. This selection bias could make predicted counterfactual treated plots appear less fire-prone than they would have been in the absence of treatment, biasing estimated treatment effects towards zero.

Another challenge stems from the survival-like nature of wildfire progression. As fires extinguish over distance, fewer plots remain for analysis beyond the initial treatment encounter (Supplementary Fig. S.1a), resulting in different sets of observations contributing to the dynamic treatment effects, τ_h. This non-random attrition reduces statistical precision, complicates the interpretation of the treatment effects [69], and could result in upward bias if surviving plots reflect atypical, extreme fire behavior.

Supplementary Fig. S.1b-d illustrates these concerns. Two patterns emerge when examining average treatment effects across larger windows of distances, h, around a fuel-treatment interaction. First, we observe modest positive pre-treatment trends

($h < 0$), indicating that treated directions are more likely to burn as fires move away from their ignition points toward fuel treatments. Second, post-treatment estimates ($h > 0$) become increasingly positive and imprecise as distance h grows, reflecting that surviving plots may disproportionately capture unrepresentative severe, persistent fire behavior.

To address these challenges, we restrict our analysis to plots within 2.5 km of the fuel-treatment interaction, thereby maintaining a relatively constant composition of plots contributing to each estimate and focusing on a localized window of plots with comparable fire dynamics [69]. Within this window, we find no evidence of differential pre-treatment trends (Supplementary Fig. S.1b). Moreover, estimates of post-treatment effects within this 2.5 km range remain stable even when expanding the window size (Supplementary Table S11).

It is important to note that all potential sources of bias—systematic treatment placement, sample selection, and non-random attrition—would attenuate our estimates toward zero by understating how severe fire behavior would have been in treated plots in the absence of fuel treatments. Thus, our estimated reductions in wildfire spread and severity should be interpreted as conservative lower bounds.

Sensitivity analysis

We conduct a range of placebo tests and robustness checks to assess the validity of our identification strategy and the sensitivity of our findings to alternative specifications and sample definitions (Supplementary Tables S4—S11). Here, we highlight several key exercises; additional analyses are reported in the Supplementary Appendix.

To further support the credibility of the parallel trends assumption, we estimate Eqs. 1 and 2 using only fires that intersect with planned-but-incomplete fuel treatment projects. If areas selected for treatment are systematically different from those that are not, we would expect spurious treatment effects to exist for treatments never implemented. In contrast, we find no evidence of effects on fire spread using this placebo sample (Extended Data Fig. 2). We do observe slightly elevated burn severity, reinforcing that fuel treatments are strategically placed in high-severity areas, and thus, our primary estimates likely represent conservative effects.

To improve comparability between treated and control plots, we conduct a matching exercise that restricts the sample to plots that are comparable in their observed characteristics (Extended Data Fig. 1 and Supplementary Table S5). The matched sample yields even larger fuel-treatment reductions in fire spread, further suggesting our baseline estimates are conservative. We also re-estimate Eq. 1 using only "yet-to-be-treated" plots from treated directions. These plots serve as a more credible control, exploiting only exogenous variation in treatment timing (or distance). Results from this restricted sample closely align with our baseline estimates, providing additional confidence in our findings.

Cumulative Effects

The treatment effects presented thus far describe how fuel treatments affect the conditional probability of a plot burning—that is, the probability that a plot burns, conditional on fire having reached it. Yet a reduction in the conditional burn probability at one location also has downstream effects: by lowering the likelihood that a fire burns a given plot, it also reduces the chance that the fire reaches and burns subsequent plots. To illustrate, suppose a fire has already burned Plot A, and let Y_i denote the conditional burn probability of Plot i. The probability that Plot B burns is Y_B, while the unconditional probability that Plot C burns is $Y_B \cdot Y_C$, since the fire must first burn through Plot B to reach Plot C. Thus, if a fuel treatment lowers the conditional burn probability in Plot B by x percentage points, then the probability that Plot C burns falls by $x \cdot Y_C$ percentage points. This compounding effect highlights how reductions in burn probability immediately after a fire encounters a fuel treatment can generate cumulative downstream benefits by interrupting the fire's progression.

To quantify the cumulative effects of fuel treatments, we construct counterfactual "survival plots," which estimate how fires would have spread in the absence of treatment. Specifically, following the preceding example, we compute unconditional burn probabilities in the absence of treatment for treated plots with distance h away from a treatment interaction. Recall that $\hat{Y}^0_{fld}$ represents a plot's predicted untreated conditional burn probability and δ_{fl} denotes the distance at which fire f and direction ℓ first intersects with a treatment. Then the counterfactual unconditional burn probability in the absence of treatment for a treated plot with distance h away from a fuel treatment, $\hat{P}^0_{flh}$, can be estimated as the product of conditional burn probabilities across distance bins:

$$\hat{P}^0_{flh} = \prod_{d=\delta_{fl}}^{\delta_{fl}+h} \hat{Y}^0_{fld}. \tag{3}$$

Similarly, we estimate a plot's unconditional expected burn severity, which is equal to its predicted conditional burn severity, $\hat{Y}^0_{fld}$, multiplied by its unconditional probability of burning:

$$\hat{BS}^0_{flh} = \hat{P}^0_{flh} \cdot \hat{Y}^0_{fl\delta_{fl}+h}. \tag{4}$$

We average these estimates for a given distance h away from a fuel treatment interaction across all fires f and treated directions ℓ and compute 95% confidence intervals using 1,000 bootstrap replications, resampling fires with replacement (Fig. 4a,b). Comparing counterfactual predictions of untreated unconditional burn probabilities and severity to their observed counterparts quantifies the cumulative effect of fuel treatments on fire spread and severity beyond the initial treatment encounter (Extended Data Fig. 3). To estimate the percent reduction in total area burned, we compute the difference between the total predicted acres burned in the absence of treatment and the total observed acres burned across all treated directions, normalized by the observed burned area.

Calculating Economic Benefits

We evaluate the cost-effectiveness of fuel treatment by estimating the expected avoided damages associated with conducting a fuel treatment, relative to its cost, given uncertainty about when and where future fires will ignite. We consider a counterfactual scenario in which the USFS did not conduct any fuel treatments between 2007 and 2023, such that there were no fuel treatments to curb the spread of fires in our sample. In total, 14,128 USFS fuel treatments were implemented during this period that could have intersected with wildfires during their effective lifetime. We use Eq. 3 to predict the counterfactual spread of fires in the absence of these fuel treatments. The estimation of expected damages under this counterfactual scenario is described below.

Ex-ante benefit-cost ratio

For each treatment i, let C_i be its cost, B_i its benefit if it intersects a fire, and I_i an indicator of intersecting with a fire in its lifetime. Assuming managers know C_i with certainty and that B_i and I_i are independent, the expected benefit-cost ratio across all treatments, $\mathcal{T}$, is:

$$\mathbb{E}[BC] = \frac{\sum_{i \in \mathcal{T}} \lambda_i \cdot \mu_i}{\sum_{i \in \mathcal{T}} C_i},$$

where $\lambda_i = \Pr(I_i = 1)$ is the probability of intersecting a fire and μ_i the expected benefit, conditional on intersecting with a fire (see the Supplementary Information for more details).

We divide treatments into terciles based on treatment size (acres), $s \in \mathcal{S} = \{75 - 600, 600 - 2400, > 2400\}$, and estimate λ_s and μ_s for each size class. We estimate λ_s using the Kaplan-Meier survival method, assuming a treatment can only intersect with one fire during its lifetime ($T = 10$ years; Extended Data Fig. 7). We estimate the expected benefit μ_s as the avoided damages due to treatment across all treatments within size class s, where a treatment's avoided damages are:

$$\hat{B}_i = \sum_{(f,l) \in \mathcal{D}_i} \sum_{d=\delta_{fl}}^{\delta_{fl}+\bar{h}} \left(\hat{P}^0_{fld} - Y_{fld} \right) \cdot Dam_{fld}.$$

The term $(\hat{P}^0_{fld} - Y_{fld}) \cdot Dam_{fld}$ represents the expected avoided damages a treated plot experienced due to being treated, which we sum up within a fire-direction up to 5 km beyond its first treatment interaction ($\bar{h} = 10$), allowing cumulative effects of treatments to perpetuate further than their direct effects (2.5 km). Total avoided damages are then calculated for the set of all fire-directions that intersect with treatment i, $\mathcal{D}_i$. The estimated average benefit of a treatment for size class s is thus $\hat{\mu}_s = \sum_{i \in \mathcal{T}_S} \hat{B}_i / N_s$, where $\mathcal{T}_s$ and N_s denote the set and number of treatments, respectively, in size class s that intersect a fire from 2017–2023. The overall ex-ante benefit-cost ratio across all treatments is thus:

$$\hat{\mathbb{E}}[BC] = \frac{\sum_{i\in\mathcal{T}} \hat{\mu}_{s(i)} \cdot \hat{\lambda}_{s(i)}}{\sum_{i\in\mathcal{T}} C_i}.$$

We also compute an ex-ante benefit-cost ratio that accounts for the opportunity cost of time by discounting a fuel treatment's expected benefits over its lifetime. We model the likelihood that a treatment interacts with a fire in a given year as a geometric process with constant annual probability $\tilde{\lambda}_{s(i)} = \hat{\lambda}_{s(i)}/T$, where T is the lifetime of a treatment. Assuming that avoided damages are constant across years and that each treatment can interact with a fire at most once during its effective lifespan, the discounted expected benefit-cost ratio is given by:

$$\hat{\mathbb{E}}^d[BC] = \frac{\sum_{i\in\mathcal{T}} \sum_{t=0}^{T-1} \hat{\mu}_{s(i)} \cdot \tilde{\lambda}_{s(i)} \cdot (1-\tilde{\lambda}_{s(i)})^t \cdot (1+r)^{-t}}{\sum_{i\in\mathcal{T}} C_i},$$

where r denotes the discount rate. The term $(1-\tilde{\lambda}_{s(i)})^t$ reflects the probability that treatment i has not interacted with a fire in years 0 through $t-1$, and thus remains eligible to provide a benefit in year t. See Supplementary Table S3 for the calculated benefit-cost ratios using different discount rates.

Estimating damages

We estimate plot-level damages, Dam_{fld}, based on two primary sources: structure loss and emissions. For structures, we count the number of structures in each plot and assume that all structures on that plot are lost if it burns. For CO_2 and $PM_{2.5}$ emissions, we assume that a fire's emissions can be attributed uniformly across a fire's burned area; hence, a plot's emissions are proportionate to the number of acres in the plot. Multiplying fire-specific estimates of CO_2 and $PM_{2.5}$ emissions (from WFEIS) by the proportion of a fire's burned area attributable to a plot provides an estimate of the CO_2 and $PM_{2.5}$ that would be emitted if a plot burns.

To monetize losses from structures, we multiply the number of structures in a plot by the median housing value in its respective Census Block Group prior to the fire. To value CO_2 emission reductions, we use a social cost of carbon estimate of $185 per ton [73]. For $PM_{2.5}$-related health damages, we use fire-specific accumulated smoke exposure estimates derived from Wen et al. [59], which represent the sum of the U.S. population exposed to each $\mu g/m^3$ of smoke $PM_{2.5}$ for each day a fire burned. To estimate the statistical lives saved, we rely on Deryugina et al. [47], who find that a 1 $\mu g/m^3$ increase in daily $PM_{2.5}$ concentrations causes 0.69 additional deaths per million individuals aged 65 and over. We scale this estimate using the national share of the population over age 65 and apply a value of a statistical life of $9.2 million [11]. Finally, we estimate $PM_{2.5}$-related productivity losses using the findings of Borgschulte et al. [11], who show that a 1 $\mu g/m^3$ increase in quarterly $PM_{2.5}$ is associated with a $103.10 per-capita reduction in earnings. We scale this estimate using county-level population and the number of quarter-days affected.

Limitations

Our analysis quantifies the economic benefits of fuel treatments, but several limitations remain. First, we do not capture all the pathways through which fuel treatments may reduce wildfire-related costs. For instance, treatments located near ignition points may prevent small fires from escalating into large, high-cost events—a mechanism shown to significantly reduce suppression expenditures [38]. We also do not account for how treatments might reduce smoke emissions through their impact on burn severity; instead, our estimated benefits only reflect treatment effects on emissions through their impact on fire spread. This likely understates smoke-related benefits, since treated areas that do burn tend to burn less severely.

In addition, we do not incorporate a broader range of economic, ecological, and social benefits such as avoided suppression costs, improved water supply and quality, revenues from thinning operations, local employment, and the non-use value of restored ecosystems [53–56]. These omissions mean that our benefit estimates should be interpreted as lower bounds on the full social benefits of fuel treatments.

While our benefit estimates are likely conservative, our treatment cost estimates may also be understated. The USFS FACTS database has known limitations, particularly for mechanical treatments, where cost data can be missing or subject to measurement error. In addition, FACTS does not account for revenues from commercial thinning operations, which often help finance non-revenue-generating fuel treatments [74]. To partially address these limitations, we also estimate treatment costs using USFS budget justifications. Specifically, we calculate the average cost per footprint acre using USFS budget data from 2011 to 2020 [75] and total footprint acres treated over the same period. We then impute treatment costs for all projects in our sample using this average cost per acre. This alternative approach yields a slightly lower benefit-cost ratio of 2.63.

At the same time, our analysis omits certain costs associated with implementing treatments, such as emissions of $PM_{2.5}$ and CO_2 during prescribed burns. A comprehensive accounting of emissions trade-offs between treated and untreated areas would require detailed modeling, which is beyond the scope of this study. However, prescribed burns are generally far less polluting than wildfires in both total emissions and public health impacts [57]. Moreover, because prescribed burns are planned events, communities can take precautionary measures to limit exposure. As a result, the health and environmental costs of smoke from prescribed burns are likely significantly outweighed by the benefits of reduced wildfire emissions.

Finally, our analysis does not account for how fuel treatments may influence the allocation of suppression resources within fires. We assume that suppression strategies would have remained unchanged in the absence of treatments, though this may not reflect real-world decision-making. This simplifying assumption overlooks potential interactions between treatment placement and suppression response that could influence our counterfactual estimates of fire behavior in the absence of treatment.

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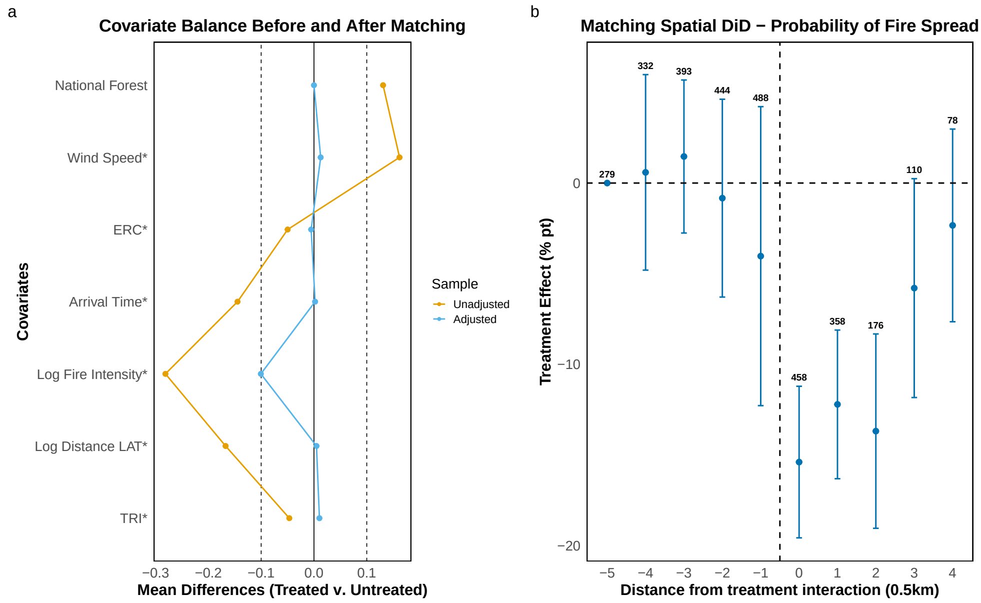
Supplementary information. Supplementary Information is available for this paper.

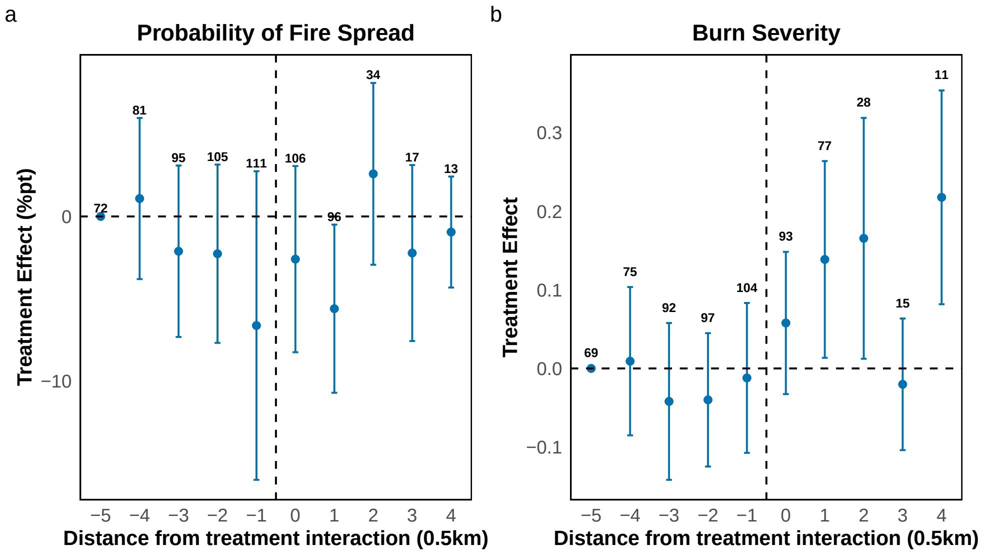
Declarations

- **Funding**: C.B. acknowledges funding from the U.S. Forest Service (project USDA-USFS-RMRS 21-CS-11221636-151).
- **Conflict of interest/Competing interests**: The authors declare no conflict of interest.
- **Ethics approval and consent to participate**: Not applicable.
- **Consent for publication**: Not applicable.
- **Data Availability**: All data used in this study are publicly available, with the exception of the LAT ATU dataset, which was provided by the U.S. Forest Service upon request. Code and data necessary to replicate the results and figures in the main text and Supplementary Information will be made available upon publication.
- **Author Contributions**: All authors contributed to the study design and writing of the manuscript. F.S. and C.B. constructed the analytical dataset; F.S. performed the data analysis, created all figures and tables, and led the empirical work.

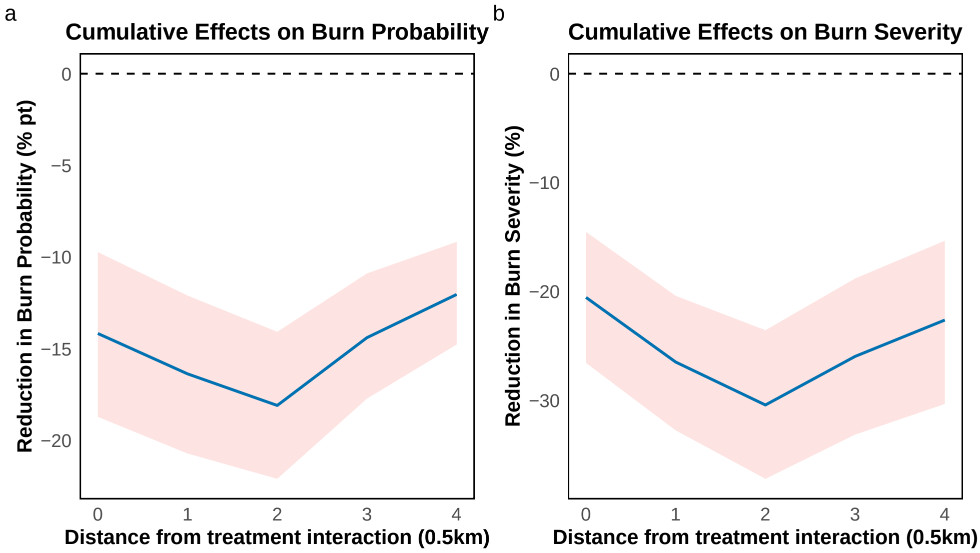
Extended Data Figures



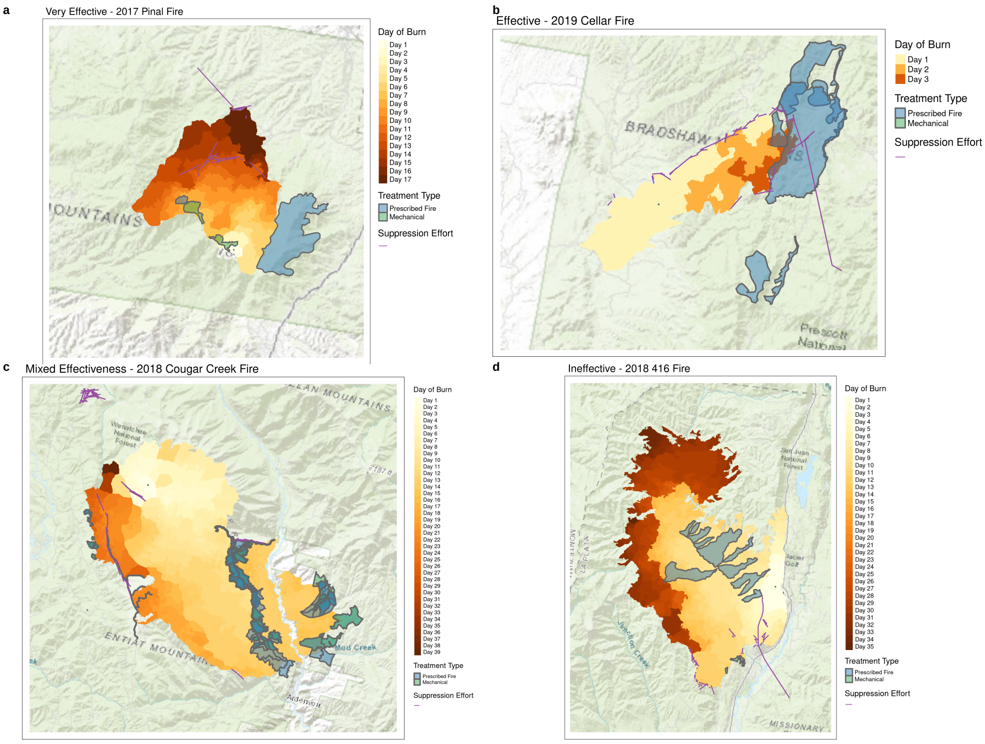
Extended Data Fig. 1: Matching results. a, Covariate balance between treated and untreated observations, before (orange) and after (blue) matching. Plots are matched through exact and inexact matching using a genetic search algorithm (the GenMatch function from the Matching package in R [76]). Plots are exactly matched to occur in the same distance bin and ownership type (National Forest or Private). Fires are inexactly matched to find the optimal covariate balance across the most important determinants of fire spread: wind speed, energy release component (ERC), arrival time (ΔT), log fire intensity and distance to large air tanker (LAT) fire retardant drop, and topographic ruggedness index (TRI). **b,** Estimated average treatment effects of fuel treatments on the conditional probability of burning using the matched sample. Numbers above each point estimate denote the number of treated observations contributing to the corresponding estimate.



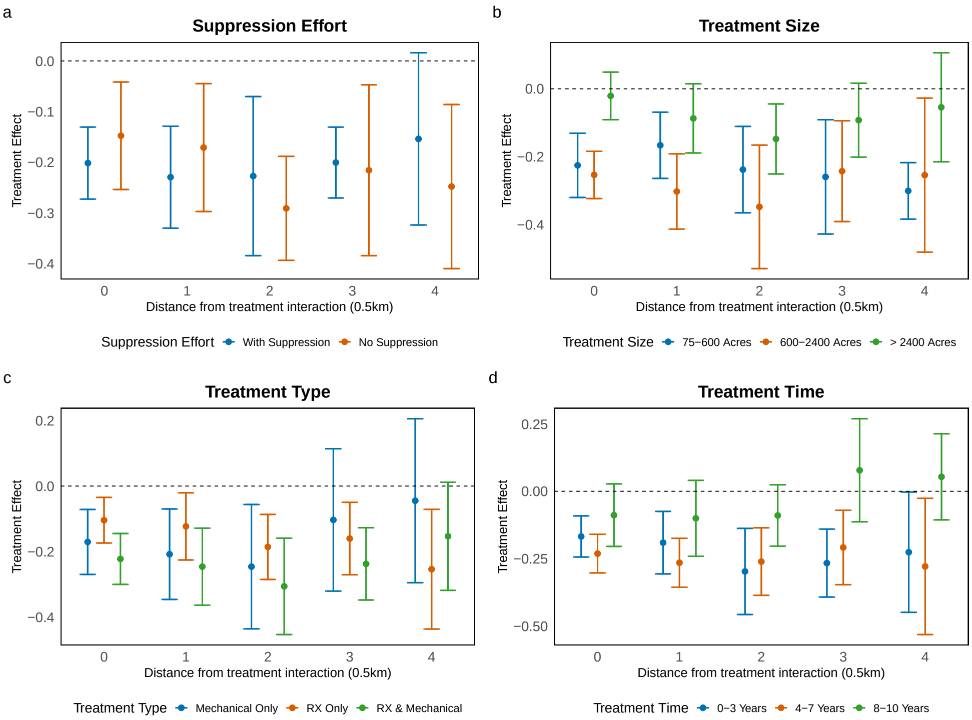
Extended Data Fig. 2: Placebo test using incomplete treatments. Estimated average treatment effects for (**a**) the conditional probability of burning and (**b**) conditional burn severity as a function of distance h from treatment interaction using a sample of incomplete fuel treatment projects as a placebo. Pre-treatment estimates are relative to the distance-from-treatment bin $h = -5$. Numbers above each estimate denote the number of treated observations contributing to the corresponding estimate.



Extended Data Fig. 3: Cumulative effect of fuel treatments on burn probability and severity. Difference between observed and estimated counterfactual (**a**) burn probability (% points) and (**b**) burn severity (%) in the absence of treatment for all treated directions. This represents the difference between "With treatment" and "Without treatment" outcomes from Figure 4. Differences in burn severity are normalized by the average burn severity without treatment to represent percentage changes. 95% confidence intervals are based on 1,000 bootstrap simulations, resampling fires with replacement.

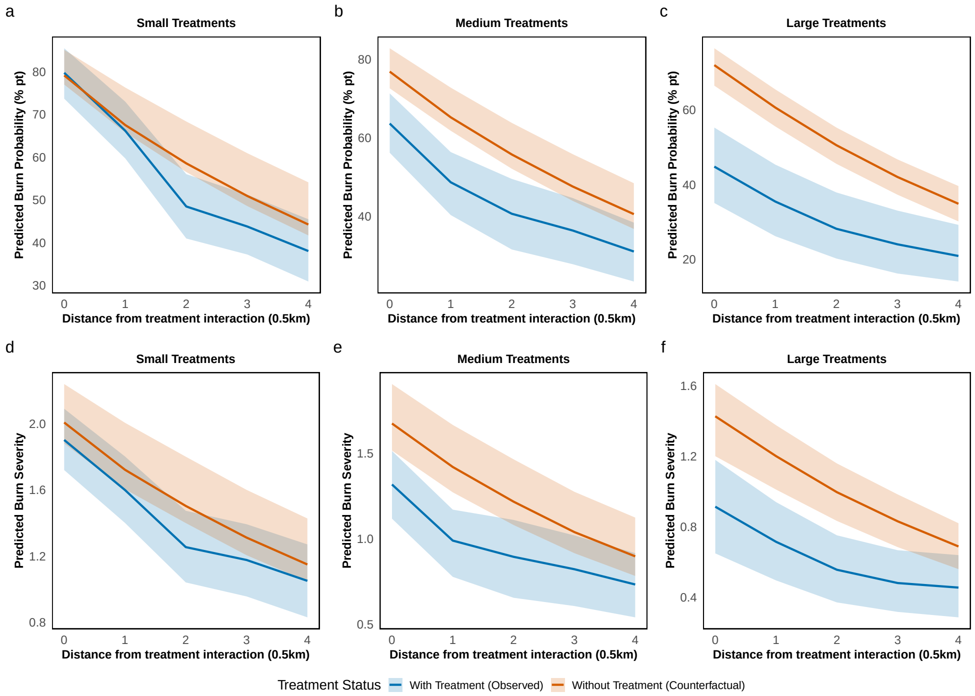


Extended Data Fig. 4: Examples of fuel treatment effectiveness. a, A highly effective prescribed burn from the 2017 Pinal Fire (Arizona). **b,** An effective prescribed burn, which received substantial fire suppression effort in the 2019 Cellar Fire (Arizona). **c,** Fuel treatments intersecting with the 2018 Cougar Creek Fire (Washington) that had mixed effectiveness. **d,** Ineffective prescribed burn treatments from the 416 Fire (Colorado).

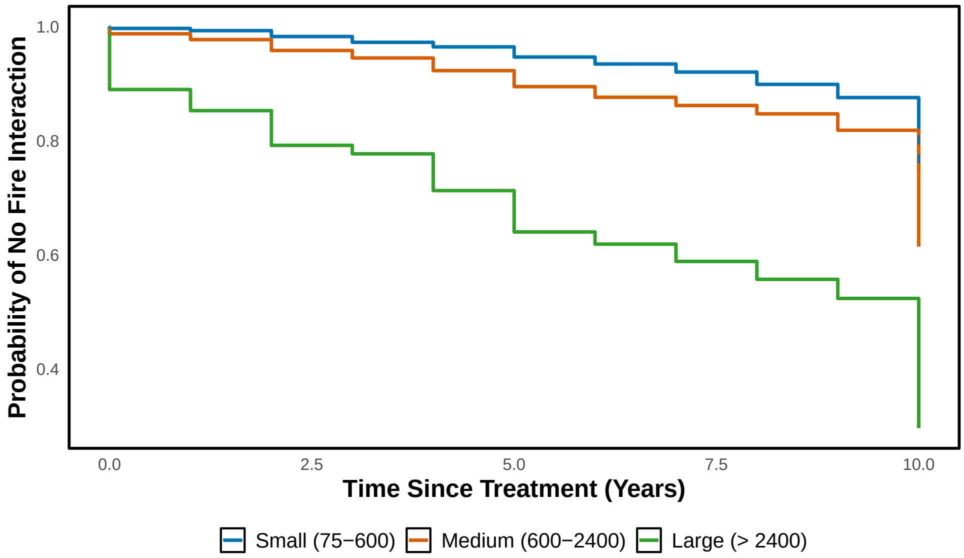


Extended Data Fig. 5: Heterogeneous treatment effects on conditional burn severity. Estimated average treatment effects of fuel treatments on conditional burn severity by **(a)** proximity to suppression resources, **(b)** treatment size, **(c)** treatment type, and **(d)** time since treatment within 2.5 km of the initial treatment-fire interaction. Treatment effects are estimated on subsamples defined by each source of heterogeneity, retaining only treated observations within each category while using the full set of never-treated observations as controls. Treatment effects in **(a)** are estimated using a subsample of 178 fires for which we have full fire suppression effort data.

Unconditional Burn Probability & Burn Severity by Treatment Size Category



Extended Data Fig. 6: Cumulative effect of fuel treatment size on fire spread and burn severity. Estimated average cumulative effects of fuel treatments on **(a-c)** the probability of burning and **(d-f)** burn severity within 2.5 km beyond the initial treatment-fire interaction for all treated directions based on fuel treatment sizes. Cumulative effects are estimated on subsamples retaining treated observations in a given treatment size category and all control observations. Treatment categories are divided into small (75-600 acres), medium (600-2400 acres), and large (> 2400 acres) size classes. "With treatment" outcomes (blue) represent averages of observed burn probability and severity. "Without treatment" outcomes (orange) represent average predicted burn probability and severity in the absence of a fuel treatment. 95% confidence intervals are based on 1,000 bootstrap simulations, resampling fires with replacement.



Extended Data Fig. 7: Probability of a treatment not interacting with a fire. Estimated probability that a fuel treatment does not interact with a wildfire within ten years of its completion, as a function of treatment size. Estimates are generated using a Kaplan-Meier survival estimator from the "survival" package in R [77] and a sample of U.S. Forest Service treatments in the Western U.S. from 2006 to 2023, which may or may not interact with wildfires from MTBS.

Supplementary Information

Data

Large Airtanker Drop Locations Data

We are provided with information from the U.S. Forest Service on the time and location of large airtanker (LAT) retardant drops. These data come from additional telemetry units (ATUs) that are mounted on LATs and automatically record the exact geographic coordinates and timestamps when the aircraft's retardant delivery doors are opened and closed. The granular nature of these data allows us to reconstruct each drop down to the meter with sub-minute temporal accuracy. The ATU dataset offers an unusually detailed account of aerial suppression operations, making it a powerful tool to analyze how and where LATs are deployed in relation to wildfires and fuel treatment projects.

Our analytic sample includes over 13,784 individual LAT retardant drops recorded across 238 unique wildfires, all located in the Western United States. These events span multiple fire seasons and include drops from both LATs, which typically carry between 2,000 and 4,000 gallons of fire retardant, and Very Large Airtankers (VLATs), capable of delivering over 8,000 gallons per drop. The spatial extent of individual drops varies substantially depending on aircraft type, terrain, and operational objectives, with drop lines ranging from a few hundred to several thousand meters in length. All drop features are spatially aligned with fire perimeters using GIS tools. This alignment enables us to compute spatial measures including the distance from a plot to the nearest drop, the proportion of the plot intersected by drop lines, and an indicator for whether a drop occurred within the plot (see Table S2).

Importantly, the LAT ATU dataset is comprehensive: all recorded large airtanker drops during the study period are included. Fires in our sample that do not contain drops represent incidents where LAT retardant was not deployed. However, the dataset does not include information on other forms of aerial suppression, such as water drops from helicopters or scooper aircraft. As a result, our analysis captures only the use of LAT-delivered retardant and does not reflect the full spectrum of aerial suppression tactics.

NIFC Containment Line Data

We obtain spatial data for on-the-ground wildfire suppression efforts from the National Interagency Fire Center (NIFC). This dataset includes georeferenced line features representing the locations of containment lines deployed during active wildfire incidents. The lines were digitized by fire personnel and incident teams and are intended to reflect the suppression infrastructure used to manage fire growth and protect assets on the landscape. Our analytic sample includes line data from 178 wildfires, allowing us to spatially characterize the use and configuration of ground-based containment strategies.

The dataset captures several distinct types of containment lines, including (i) hand-dug lines from firefighters, (ii) machine-dug lines from machinery such as dozers or plows, (iii) roads used for containment, (iv) burnout operations, or (v) fuel breaks from an undetermined source. These different types of containment reflect differences in construction methods, tactical objectives, and deployment context. All line features are spatially projected and aligned with fire progression and drop data using GIS processing tools. This alignment enables us to compute key spatial measures, including a plot's distance to the nearest containment line, the proportion of the plot intersected by containment features, and an indicator for whether a containment line crosses the plot (see Table S2).

Implementing Minimum Travel Time Simulations

We utilize outputs from the Minimum Travel Time (MTT) algorithm, implemented via the FlamMap software suite, to control for predictable patterns of fire behavior for the 285 wildfires in our sample [67]. MTT is a deterministic fire spread model that calculates the fastest routes of fire growth across a landscape by solving for the minimum travel time between an ignition point and every other location, based on spatial variation in fuels, topography, and weather conditions. It provides a computationally efficient way to simulate potential fire spread pathways under a fixed set of input conditions. MTT serves as a tool to control for variation in potential fire behavior in the absence of fuel treatment, allowing us to isolate the effect of treatment on wildfire outcomes.

It is important to emphasize that we do not use MTT to predict final fire perimeters. The model is not well-suited for such applications: in simulation settings where the user specifies a fixed duration, the final perimeter is often highly sensitive to this duration choice. Rather, we leverage MTT's ability to simulate fire behavior across the full spatial extent of a fire-prone landscape. Compared to alternative models such as FARSITE, MTT allows for simulations to proceed until fire behavior is predicted for every cell in the defined landscape extent—regardless of time. This feature is critical for our setting, where we analyze spatially disaggregated fire behavior within sectors of a circular grid. A limitation of MTT is that it does not support time-varying weather; instead, the user must specify a constant wind speed and direction throughout the simulation.

To simulate fire behavior on the landscapes surrounding the 285 wildfire ignitions in our sample, we use TestMTT, a command-line implementation of the MTT model that leverages the FlamMap software suite.[1] The command-line interface allows efficient execution of a large number of fire simulations in a batch-processing environment. Inputs to TestMTT include an ignition shapefile, a landscape file, specifications of fuel and weather conditions, and additional optional simulation parameters.

For each fire, we define ignition locations as the centroid of the Day 1 fire perimeter polygon, buffered by 60 meters to reflect initial fire area and ensure compatibility with raster inputs. Simulation landscape are $K \times K$ kilometer areas centered at the fires origin, where K corresponds to the maximum observed spread distance of the fire from its ignition point, plus a 3-kilometer buffer in all directions.

We crop 30-meter resolution raster layers to these landscapes, representing topographic (elevation, slope, aspect) and vegetation conditions, drawing on LANDFIRE

[1]TestMTT is available for download from https://www.alturassolutions.com/FB/FB_API.htm, FlamMap from https://research.fs.usda.gov/firelab/products/dataandtools/flammap.

datasets. Vegetation layers include Scott and Burgan standard fire behavior fuel models, canopy cover, canopy height, canopy base height, and canopy bulk density (see Table S2 for detailed descriptions). To estimate counterfactual fire behavior in the absence of treatment, we fix vegetation conditions to reflect those from the year 2001—i.e. LANDFIRE 2001.

Wind speed and direction are extracted from the gridMET dataset for the date and location of each fire's ignition. These values are assumed to be constant throughout the simulation. TestMTT requires inputs for fuel moisture content for five fuel types: 1-hour, 10-hour, and 100-hour dead fuels, and live herbaceous and woody fuels. Because retrospective, spatially resolved estimates of fuel moisture are unavailable for all fuel classes, we follow prior literature (e.g., Plantinga et al. [24]) and use FlamMap's default "moderate" values: 6%, 7%, and 8% for 1, 10, and 100-hour dead fuels, respectively; 60% for live herbaceous fuels; and 90% for live woody fuels.[2] Since our analysis focuses on relative fire behavior across space and treatment status—rather than absolute predictions of spread rates—our results are not likely to be highly sensitive to this choice of fuel moisture parameters.

Simulations are conducted at a 150-meter spatial resolution. We use default FlamMap parameters for all other fire behavior submodels, including those governing crown fire activity, wind adjustment factors, and fire spotting.

From each simulation, we extract two key outputs: fire arrival time and fireline intensity. Arrival time measures the number of hours after ignition that the fire is predicted to reach each plot's centroid, while fireline intensity captures the predicted heat output per unit time. We calculate each plot's average arrival time (T_{ld}), and compute $\Delta T_{ld} = T_{ld} - T_{l,d-1}$ as a measure of the rate of predicted fire spread. We also create an indicator of whether ΔT_{ld} is missing which may be because either the focal cell or previous cell is missing fuels in the majority of its area or because time of arrival is predicted to be lower in the focal cell than the previous cell. Lastly, we calculate the average of the natural log of fireline intensity in a plot.

Ex-Ante Benefit-Cost Ratio Derivation

To evaluate the cost-effectiveness of fuel treatments, we ask a central policy question: What are the expected benefits of conducting a fuel treatment—measured as reduced wildfire damages—relative to its cost, given uncertainty about where future fires will ignite and spread to?

Crucially, land managers must decide where to implement treatments without knowing if or when a wildfire will occur in that location. Simply comparing the benefits of treatments that happened to intersect with fires to their costs ignores this uncertainty and overstates expected returns. Instead, we estimate an ex-ante benefit-cost ratio: a forward-looking measure that accounts for the probability that a treatment intersects with a fire during its effective lifetime.

To formalize this idea, let C_i denote the cost of implementing treatment i and B_i the benefit it provides if it intersects with a fire. Let I_i denote a dummy variable that is equal to one if fuel treatment i intersects with a fire in its lifetime and zero otherwise.

[2] These defaults are frequently used in retrospective simulation settings where detailed fuel moisture data are unavailable.

Assuming a treatment can intersect with at most one fire, the realized benefit-cost ratio is:

$$BC_i = I_i \times \frac{B_i}{C_i}.$$

Since managers don't know B_i and I_i at the time of implementation we instead calculate the expected benefit-cost ratio. Assuming B_i and I_i are independent, this expectation becomes:

$$\mathbb{E}[BC_i] = \Pr[I_i = 1] \times \frac{\mathbb{E}[B_i]}{C_i} = \frac{\lambda_i \cdot \mu_i}{C_i},$$

Here $\lambda_i = \Pr[I_i = 1]$ is the probability that treatment i intersects with a fire $\mu_i = \mathbb{E}[B_i]$ is its expected benefit conditional on intersection.

We then estimate the average ex-ante benefit-cost ratio across all treatments that could have been conducted during our sample time period, $\mathcal{T}$, as:

$$\mathbb{E}[BC] = \frac{\sum_{i \in \mathcal{T}} \lambda_i \mu_i}{\sum_{i \in \mathcal{T}} C_i}.$$

This serves as our basis for estimating the expected avoided damages described in Section 2.

Robustness Checks Explanation

We conduct a series of robustness checks to evaluate the sensitivity of our results to alternative control groups, specifications, sample, and sample constructions. To address concerns that treated and control directions may differ systematically—even after conditioning on observable determinants of fire behavior—we: (i) implement a matching procedure to improve comparability between treated and control plots; (ii) estimate treatment effects using only treated directions; and (iii) exclude all control directions adjacent to treated directions (Table S5). We remove adjacent control directions to mitigate concerns about potential violations of the Stable Unit Treatement Value Assumption (SUTVA), whereby fuel treatments may induce fire flanking into nearby plots, potentially increasing burn probability and severity in those adjacent controls [40].

Estimates from (i) and (ii) yield larger and statistically significant treatment effects, suggesting that our baseline DiD specification likely underestimates the true effect of fuel treatments on fire spread (Table S5). While the matched estimates provide stronger internal validity, we favor the baseline DiD specification because its sample more closely reflects the broader landscape in which treatments occur—making it more suitable for the counterfactual cost-benefit analysis. We also prefer the baseline over the treated-only specification because including control directions improves the model's ability to make out-of-sample predictions required for our counterfactual exercise. Finally, results from (iii) are nearly identical to the baseline, suggesting that any potential SUTVA violations from adjacency are minimal in our context.

We also explore the sensitivity of our results to the number of directions used to construct our sample. Since we use a linear probability model to model the hazard rate, our baseline results do not require independence across directions to achieve unbiasedness or consistency [78]. In Table S6, we show how the results change as the number of directions included in the sample varies. As expected, we find that as the number of directions decreases, both the magnitude and statistical significance of the estimates attenuate due to reduced precision and aggregation bias. However, the results remain broadly similar across the columns, indicating that our choice of directions does not substantially influence the overall findings.

We further explore whether our results are driven by variation in fire suppression effort, particularly the possibility that suppression is strategically deployed near fuel treatments, driving the results. In Table S7, we show how estimated treatment effects change with the inclusion of suppression controls. These include indicators for the presence and proximity of LAT drops across the full sample and fireline controls for the subset of 178 fires with detailed fireline data. We find that including suppression effort controls does not substantially alter the estimated treatment effects. Column 6 further restricts control plots to those located within 0.2 km of either a LAT drop or a fireline. The results from this restricted sample are slightly more negative and more statistically significant, supporting the interpretation that fuel treatments enhance the effectiveness of suppression.

We also test the sensitivity of our results to the definition and construction of the sample. In our baseline sample, we define fire origins as the centroid of the perimeter on the first day the fire burned. In Column 2 of Table S11, we use ignition locations as reported by MTBS instead and find similar treatment effect estimates. We then examine three sample restrictions: (i) limiting to fires ignited by lightning; (ii) removing plots located outside of USFS-managed Wilderness within National Forests (i.e., excluding private, Wilderness, or other federal lands); and (iii) excluding plots where fire behavior is potentially non-contiguous—for example, when a plot's adjacent neighbor closer to the fire origin did not burn, but a more distant plot in the same direction did. The results from the lightning-only subsample, which relies on more quasi-random ignition locations, are consistent with our baseline estimates, lending additional support to our identification strategy. Similarly, restricting the sample to USFS-managed lands shows that our findings are not driven by differences in ownership or land management context. Lastly, removing plots with potentially unusual fire behavior (iii) helps account for fire direction changes and flanking dynamics; results from this subsample remain consistent with the main estimates.

We also evaluate the robustness of our findings to alternative difference-in-differences estimators. Table S9 presents results from (i) the Sun and Abraham estimator [70], (ii) the Callaway and Sant'Anna estimator [79], and (iii) a standard two-way fixed effects (TWFE) estimator. Across all approaches, we find treatment effects that are similar in magnitude and significance to our baseline specification. In some cases, these alternative estimators yield even stronger effects, suggesting that our findings are not sensitive to the specific choice of DiD estimation strategy.

Finally, we examine the sensitivity of our results to alternative definitions of treatment exposure. In our baseline specification, a plot is defined as treated if at least 50% of its area overlaps with a fuel treatment. This threshold is intended to avoid misclassifying plots as treated when only a small portion of the area contains treatment. In Table S10, we report results using alternative thresholds: any overlap (>0%), 25%, 50%, 75%, and 100%. Across all definitions, we continue to find statistically significant treatment effects. As expected, the magnitude of the estimates attenuates when the threshold is either more permissive or more restrictive, likely due to increased measurement error or a reduced sample size.

Supplementary Figures

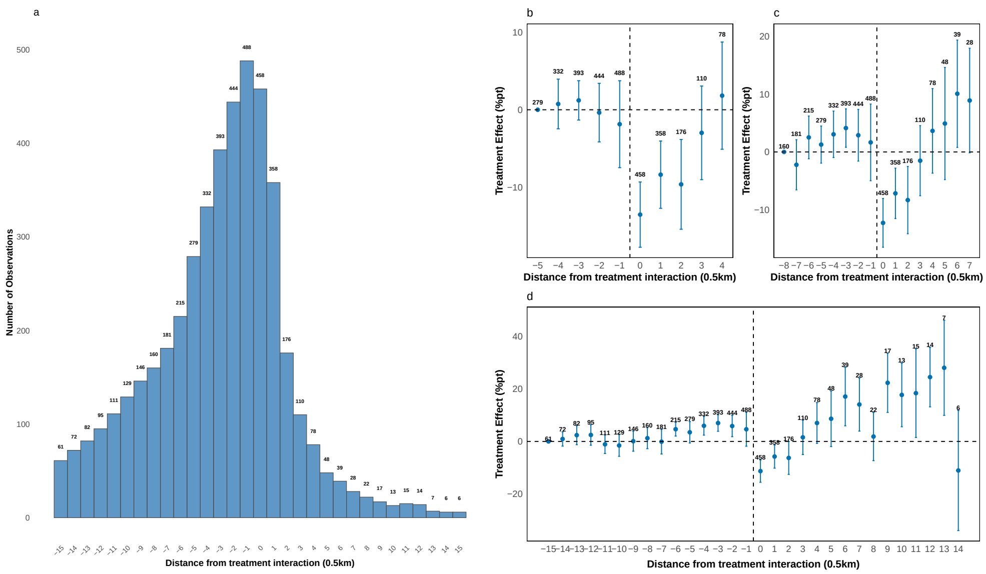


Fig. S.1: **Event Study Plots by Event Window**: Panel **a**) displays the distribution of the number of treated observations across different distances to the nearest distance bin containing the first treatment in its direction. Panels **b-d**) show the event study coefficient estimates on the probability of fire spread for 2.5, 4, 7 kilometer event windows. Numbers above each coefficient estimate display the number of treated observations used to estimate the corresponding coefficient. Event study plots are calculated via the Borusyak et al. [25] method for accounting for unit and time specific heterogeneous treatment effects.

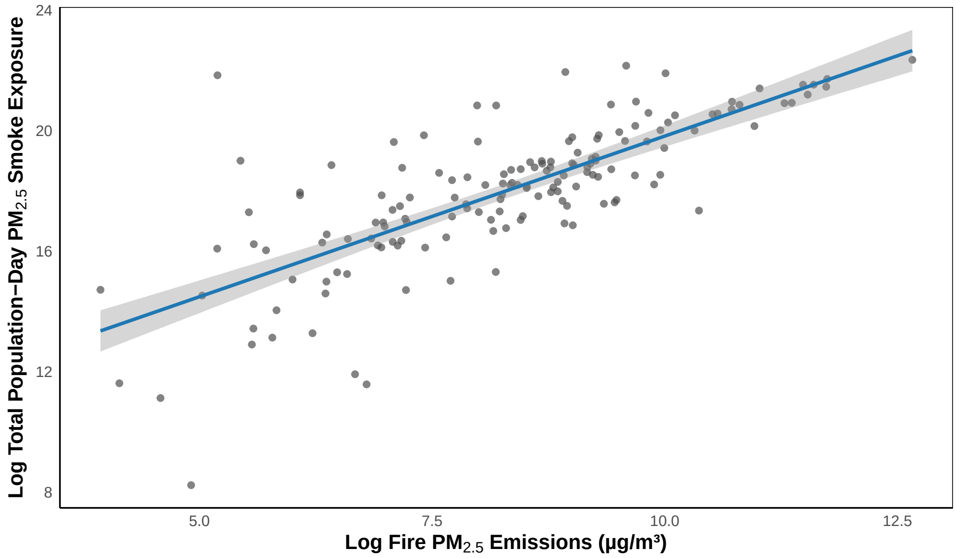


Fig. S.2: **Relationship Between Fire $PM_{2.5}$ Emissions and Population-Day $PM_{2.5}$ Exposure**: Relationship between the natural log of total $PM_{2.5}$ emissions and the natural log of total population-day $PM_{2.5}$ exposure for wildfires occurring from 2017 to 2020. Emissions estimates are from WFEIS, and exposure estimates are from Wen et al. (2023) [59].

Supplementary Tables

Table S1: Main Variables & Data Sources

Category	Variables	Sources
Fires	Wildfire perimeters, burn severity	MTBS
	Day of burn	Parks (2014) [60]
Fuel Treatments	Treatment polygons, cost, & treatment type	FACTS USFS [80]
Institutional Variables	Distance to WUI & US Highway	Radeloff et al. [65], U.S. Census Bureau [81]
	USFS road, National Forest & Wilderness Areas	USFS [66, 82, 83]
Assets at Risk	Structures, Homes, & Median Housing Values	Jaffe et al. (2024) [68] & ACS
Suppression Effort	Large air tanker (LAT) drop	USFS
	Firelines	NIFC
Topography	Slope, Aspect, Elevation, Topographic ruggedness index	LANDFIRE
Weather	Wind speed & direction 1000 hour fuel moisture, ERC	gridMET
Vegetation Characteristics	Fuel type group & canopy characteristics	LANDFIRE
Fire Simulation Outputs	Arrival time, fireline intensity	MTT Simulations in FlamMap
Historic Fire Risk	Mean Fire Return Interval (MFRI)	LANDFIRE
	Previous wildfire area burned	MTBS
Smoke	Fire CO_2 & $PM_{2.5}$ Emissions	WFEIS
	Population-day weighted $PM_{2.5}$ exposure	Wen et al. [59]

Note: USFS = United States Forest Service, FACTS = Forest Activity Tracking System, WUI = Wildland Urban Interface, ACS = American Community Survey MTT = Minimum Travel Time, NIFC = National Interagency Fire Center, WFEIS = Wildland Fire Emissions Inventory System

Table S2: Control Variable Names, Descriptions, & Sources

Name	Definition	Source
Topographic Variables		
Slope	The average slope percent of a plot	LANDFIRE
Elevation	The average elevation (ft) of a plot	LANDFIRE
Aspect Class	8 aspect classes based on cardinal directions (see https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/how-aspect-works.htm)	LANDFIRE
TRI	Terrain Ruggedness Index (TRI), constructed using elevation data from LANDFIRE and ‘terrain()‘ from R package `terra`	LANDFIRE
Historic Fire Risk & Vegetation Characteristics		
Previously Burned	Equals 1 if a plot's centroid burned in the previous ten years	MTBS
MFRI	Avg Mean Fire Return Interval (MFRI) of a plot, MFRI is the average period between fires under historic regimes	LANDFIRE
Fuel Group Type	Fuel type a plot's centroid as per the 13 Anderson models	LANDFIRE
Canopy Bulk Density	Available canopy fuel density (kg/m^3 $\times$ 100), used in MTT simulations	LANDFIRE
Canopy Height	Vegetation canopy top height (m $\times$ 10), used in MTT simulations	LANDFIRE
Canopy Base Height	Canopy bottom height from ground (m $\times$ 10), used in MTT simulations	LANDFIRE
Canopy Cover	Tree canopy percent cover in a stand, used in MTT simulations	LANDFIRE
Weather Variables		
Wind Speed	Avg wind speed (m/s) on day of burn at plot centroid	gridMET
Wind Direction	Avg wind direction (degrees) on day of burn at plot centroid	gridMET
Wind Difference	Cosine of directional difference between grid bearing and avg wind direction on day the previous cell burned	gridMET
ERC	Avg energy release component on day of burn at plot centroid	gridMET
FM 1000	Avg 1000-hour fuel moisture (%) on day of burn at plot centroid	gridMET

Name	Definition	Source
Fire Suppression Effort & Determinants of Suppression Effort		
LAT & Distance LAT	Indicator for LAT drop and distance to nearest LAT drop	USFS
Sup Line & Distance to Sup Line	Indicator if a plot contains a suppression line and distance to nearest suppression line	NIFC
Sup Line Intensity	The total length of suppresison lines divided by total acres in a plot	NIFC
LAT Line Intensity	The total length of LAT lines divided by total acres in a plot	NIFC
Distance WUI	Distance to nearest U.S. Census WUI block	[65]
Distance USFS Road	Distance to nearest USFS road	[66]
Distance US Highway	Distance to nearest U.S. Highway	[81]
Fire Simulation Outputs		
ΔT	Difference in simulated time of arrival between current and previous cells (hours)	MTT Outputs
ΔT Missing	Equals 1 if ΔT is missing. ΔT can be missing either because the target cell or previous cell is missing fuels in the majority of its area or because time of arrival is predicted to be lower in the target cell than the previous cell.	MTT Outputs
Fireline Intensity	Log of simulated fire intensity (kW/hour)	MTT Outputs
Ownership		
National Forest	Dummy for plot centroid inside National Forest	[83]
Wilderness Area	Dummy for plot centroid inside a Wilderness Area	[82]
WUI	Dummy for plot centroid inside WUI	[65]

Note: USFS = United States Forest Service, FACTS = Forest Activity Tracking System, WUI = Wildland Urban Interface, MTT = Minimum Travel Time, NIFC = National Interagency Fire Center

Table S3: Estimated Benefit-Cost Ratios by Discount Rate

Discount Rate	Small	Medium	Large	Total
0	2.7	3.26	5.03	3.48
0.03	2.29	2.6	3.49	2.7
0.05	2.1	2.4	3.24	2.49
0.08	1.87	2.14	2.92	2.23

Note: Estimated benefit–cost ratios for small (75–600 acres), medium (600–2400 acres), and large (>2400 acres) treatments, as well as the overall benefit–cost ratio, reported by discount rate.

Table S4: Spatial DiD - Baseline Regressions

	Probability of Fire Spread (1)	Conditional Burn Severity (2)
$Treat_0$	-0.135***	-0.177***
	(0.021)	(0.032)
$Treat_1$	-0.084***	-0.202***
	(0.022)	(0.043)
$Treat_2$	-0.096***	-0.251***
	(0.030)	(0.055)
$Treat_3$	-0.030	-0.186***
	(0.031)	(0.065)
$Treat_4$	0.018	-0.174*
	(0.035)	(0.090)
Observations	69,174	61,616
R^2	0.45	0.88

*p $<$ 0.10; **p $<$ 0.05; ***p $<$ 0.01.

The table presents results from two separate Spatial Difference-in-Differences (DiD) regressions. The first column estimates the impact of fuel treatments on the probability of fire spread, conditional on a plot not yet being extinguished, while the second column estimates its impact on burn severity conditional on a plot burning. The coefficient, $Treat_k$, captures the estimated effect of a fuel treatment located k distance bins (0.5 km each) from where the fire first encounters the treatment in a given direction. Each sample comprises of plots from wildfires that intersect with USFS fuel treatments between 2017 and 2023. Treated plots that are more than 2.5 km away from where a fire first interacts with a treatment in a given direction are excluded. In Column 1, the sample is restricted to plots that are not yet extinguished—specifically, where the plot one distance bin closer to the fire origin in its given direction has burned. In Column 2, the sample is restricted to plots that burn. Each regression includes fire-direction and distance-bin fixed effects, along with controls for environmental conditions, economic factors, and suppression efforts. Economic controls include distance to a WUI Census Block, USFS road, and US Highway, as well as indicators for whether the plot is within the WUI, a USFS National Forest, or a Wilderness Area. Environmental controls account for historic fire risk (whether a plot burned in the previous ten years and its historic mean fire return interval), topographic characteristics (slope, elevation, aspect class, and topographic ruggedness), weather conditions on the day of burning (energy release component, 1000-hour fuel moisture, wind speed, and wind difference), and fire simulation outputs (ΔT, ΔT missing, and the natural log of fire intensity). Suppression effort controls include an indicator for whether a plot received a large-air tanker (LAT) drop and its distance to the nearest LAT drop. Spatial DiD coefficient estimates are obtained using the imputation approach from [25], implemented via the "didimputation" package in R [84]. Standard errors are clustered at the fire level.

Table S5: Spatial DiD Robustness Check - Different Control Groups

	Probability of Fire Spread			
	(1)	(2)	(3)	(4)
$Treat_0$	-0.135***	-0.154***	-0.139***	-0.135***
	(0.021)	(0.021)	(0.022)	(0.022)
$Treat_1$	-0.084***	-0.122***	-0.078***	-0.081***
	(0.022)	(0.021)	(0.021)	(0.022)
$Treat_2$	-0.096***	-0.137***	-0.111***	-0.094***
	(0.030)	(0.027)	(0.027)	(0.030)
$Treat_3$	-0.030	-0.058*	0.023	-0.028
	(0.031)	(0.031)	(0.023)	(0.031)
$Treat_4$	0.018	-0.023	-0.008	0.021
	(0.035)	(0.027)	(0.029)	(0.036)
Baseline	Yes	No	No	No
Matched Sample	No	Yes	No	No
Treated Directions Only	No	No	Yes	No
No Adjacent Directions	No	No	No	Yes
Direction-Fire FEs	Yes	Yes	Yes	Yes
Distance FEs	Yes	Yes	Yes	Yes
Observations	69,174	4,306	3,116	63,128
R^2	0.45	0.91	0.87	0.46

*p < 0.10; **p < 0.05; ***p < 0.01.
The table presents results from four separate Spatial Difference-in-Differences (DiD) regressions estimating the impact of fuel treatments on the probability of fire spread, conditional on a plot not yet being extinguished. Each regression is estimated on a different sample, varying by the choice of control groups. The coefficient, $Treat_k$, captures the estimated effect of a fuel treatment located k distance bins (0.5 km each) from where the fire first encounters the treatment in a given direction. All samples include wildfires that intersect with USFS fuel treatments between 2017 and 2023, and observations treated more than 2.5 km away are excluded. Column 1 reports estimates using the baseline sample, where plots that are either never treated directions or "yet-to-be treated" plots serve as counterfactuals. Column 2 presents results on a matched subsample, constructed to improve comparability between treated and control plots (see Extended Data Fig. 1 for details). Column 3 removes all never-treated directions, using only "yet-to-be treated" plots as the counterfactual and Column 4 uses a sample that excludes also control directions adjacent to treated directions. Each regression includes fire-direction and distance-bin fixed effects, along with controls for environmental conditions, economic factors, and suppression efforts as detailed in Table S4. Standard errors are clustered at the fire level. Spatial DiD estimates are estimated using the imputation approach from [25] using the "didimputation" [84] package in R.

Table S6: Spatial DiD Robustness Check - Changing No. Directions

	Probability of Fire Spread			
	(1)	(2)	(3)	(4)
$Treat_0$	-0.131***	-0.135***	-0.120***	-0.042**
	(0.021)	(0.021)	(0.022)	(0.018)
$Treat_1$	-0.096***	-0.084***	-0.039*	-0.037*
	(0.019)	(0.022)	(0.022)	(0.021)
$Treat_2$	-0.028	-0.096***	-0.030	-0.051*
	(0.026)	(0.030)	(0.027)	(0.027)
$Treat_3$	-0.012	-0.030	-0.006	-0.022
	(0.031)	(0.031)	(0.031)	(0.037)
$Treat_4$	-0.024	0.018	-0.052	0.005
	(0.031)	(0.035)	(0.038)	(0.044)
No. Directions	36	24	18	12
Observations	102,301	69,174	51,709	34,571
R^2	0.40	0.45	0.49	0.57

*p < 0.10; **p < 0.05; ***p < 0.01.

The table presents results from four separate Spatial Difference-in-Differences (DiD) regressions estimating the impact of fuel treatments on the probability of fire spread, conditional on a plot not yet being extinguished. Each regression is estimated on a different sample, varying by the choice of the number of directions in the construction of our sample (36, 24, 18, 12). The coefficient, $Treat_k$, captures the estimated effect of a fuel treatment located k distance bins (0.5 km each) from where the fire first encounters the treatment in a given direction. All samples include wildfires that intersect with USFS fuel treatments between 2017 and 2023, and observations treated more than 2.5 km away are excluded. Each regression includes fire-direction and distance-bin fixed effects, along with controls for environmental conditions, economic factors, and suppression efforts as described in Table S4. Spatial DiD estimates are estimated using the imputation approach from [25] using the "didimputation" [84] package in R. Standard errors are clustered at the fire level.

Table S7: Spatial DiD Robustness Check - Impact of Suppression Controls

	Probability of Fire Spread					
	(1)	(2)	(3)	(4)	(5)	(6)
$Treat_0$	-0.135***	-0.138***	-0.115***	-0.112***	-0.108***	-0.161***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
$Treat_1$	-0.084***	-0.085***	-0.067***	-0.067***	-0.062***	-0.124***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)	(0.034)
$Treat_2$	-0.096***	-0.097***	-0.086***	-0.087***	-0.081***	-0.222***
	(0.030)	(0.030)	(0.030)	(0.029)	(0.028)	(0.041)
$Treat_3$	-0.030	-0.029	-0.050	-0.051	-0.045	-0.118
	(0.031)	(0.031)	(0.033)	(0.033)	(0.032)	(0.080)
$Treat_4$	0.018	0.020	0.035*	0.033*	0.037**	0.019
	(0.035)	(0.035)	(0.018)	(0.018)	(0.018)	(0.022)
Baseline	Yes	No	No	No	No	No
LAT Controls	Yes	No	No	Yes	Yes	Yes
Suppression Line Controls	No	No	No	No	Yes	Yes
Full Sample	Yes	Yes	No	No	No	No
Suppression Line Sample	No	No	Yes	Yes	Yes	Yes
Effort Only Controls	No	No	No	No	No	Yes
Observations	69,174	69,174	45,824	45,824	45,824	18,217
No. Fires	285	285	178	178	178	178
R^2	0.45	0.45	0.46	0.46	0.46	0.46

*p < 0.10; **p < 0.05; ***p < 0.01.
The table presents results from four separate Spatial Difference-in-Differences (DiD) regressions estimating the impact of fuel treatments on the probability of fire spread, conditional on a plot not yet being extinguished. Each regression is estimated on a different sample or set of fire suppression controls to assess the sensitivity of our results to their inclusion. The coefficient, $Treat_k$, captures the estimated effect of a fuel treatment located k distance bins (0.5 km each) from where the fire first encounters the treatment in a given direction. Column 1 reports estimates based on our baseline sample, including large-air tanker (LAT) drop controls, while column 2 reports estimates from this sample without these controls. Columns 3-6 use a sample of fires for which we have data on fire lines. Column 3 includes no suppression effort controls, column 4 includes LAT drop controls, and column 5 includes both LAT drop and fire suppression line controls. Column 6 includes only controls which are "close" to fire suppression efforts. We define a plot as "close" to suppression resources if it is within 0.2 kilometers of a large airtanker (LAT) drop or a fireline, while plots are "far" from suppression resources if they are further than 0.2 kilometers of both. Each regression includes fire-direction and distance-bin fixed effects, along with controls for environmental conditions and economic factors, as detailed in Table S4. Spatial DiD estimates are estimated using the imputation approach from [25] using the "didimputation" [84] package in R. Standard errors are clustered at the fire level.

Table S8: Spatial DiD Robustness Check - Alternative Samples

	Probability of Fire Spread				
	(1)	(2)	(3)	(4)	(5)
$Treat_0$	-0.135***	-0.112***	-0.143***	-0.130***	-0.077***
	(0.021)	(0.027)	(0.023)	(0.021)	(0.030)
$Treat_1$	-0.084***	-0.092***	-0.057**	-0.093***	-0.132***
	(0.022)	(0.022)	(0.023)	(0.022)	(0.038)
$Treat_2$	-0.096***	-0.054*	-0.108***	-0.090***	-0.178***
	(0.030)	(0.032)	(0.033)	(0.030)	(0.058)
$Treat_3$	-0.030	0.007	-0.026	0.011	-0.029
	(0.031)	(0.035)	(0.034)	(0.032)	(0.036)
$Treat_4$	0.018	-0.005	0.022	0.043	0.075
	(0.035)	(0.046)	(0.041)	(0.034)	(0.082)
Baseline	Yes	No	No	No	No
Reported Ignitions	No	Yes	No	No	No
USFS - Non-Wilderness	No	No	Yes	No	No
No Already Extinguished	No	No	No	Yes	No
Lightning Only	No	No	No	No	Yes
Direction-Fire FEs	Yes	Yes	Yes	Yes	Yes
Distance FEs	Yes	Yes	Yes	Yes	Yes
Observations	69,174	78,848	48,560	61,652	20,605
R^2	0.45	0.41	0.53	0.47	0.46

*p < 0.10; **p < 0.05; ***p < 0.01.
The table presents results from five separate Spatial Difference-in-Differences (DiD) regressions estimating the impact of fuel treatments on the probability of fire spread, conditional on a plot not yet being extinguished. Each regression is estimated on a different sample. The coefficient, $Treat_k$, captures the estimated effect of a fuel treatment located k distance bins (0.5 km each) from where the fire first encounters the treatment in a given direction. All samples include wildfires that intersect with USFS fuel treatments between 2017 and 2023, and observations treated more than 2.5 km away are excluded. Column 1 reports estimates based on our baseline sample, while column 2 uses a sample constructed from reported ignition locations from MTBS. Column 3 excludes plots located within wilderness areas or outside USFS National forests. Column 4 excludes plots in directions where the fire had already been extinguished—that is, once the fire fails to spread into the next adjacent plot further from the origin, all subsequent plots in that direction are removed from the sample. Column 5 includes only fires starting by lightning. Each regression includes fire-direction and distance-bin fixed effects, along with controls for environmental conditions, economic factors, and suppression efforts, as detailed in Table S4. Spatial DiD estimates are estimated using the imputation approach from [25] using the "didimputation" [84] package in R. Standard errors are clustered at the fire level.

Table S9: Spatial DiD Robustness Check - Alternative DiD Estimators

	Probability of Fire Spread			
	(1)	(2)	(3)	(4)
$Treat_0$	-0.135***	-0.129***	-0.120***	-0.121***
	(0.021)	(0.024)	(0.045)	(0.036)
$Treat_1$	-0.084***	-0.045*	-0.103***	-0.134***
	(0.022)	(0.027)	(0.038)	(0.033)
$Treat_2$	-0.096***	-0.099***	-0.135***	-0.180***
	(0.030)	(0.035)	(0.041)	(0.042)
$Treat_3$	-0.030	-0.099***	-0.075*	-0.150***
	(0.031)	(0.036)	(0.040)	(0.048)
$Treat_4$	0.018	-0.018	-0.053	-0.143***
	(0.035)	(0.045)	(0.041)	(0.043)
Baseline	Yes	No	No	No
Sun & Abraham	No	Yes	No	No
Callaway & Sant'Anna	No	No	Yes	No
Standard TWFE	No	No	No	Yes
Observations	69,174	69,174	69,174	69,174

*p $<$ 0.10; **p $<$ 0.05; ***p $<$ 0.01.

The table presents results from four separate Spatial Difference-in-Differences (DiD) regressions estimating the impact of fuel treatments on the probability of fire spread, conditional on a plot not yet being extinguished. Each regression applies a different DiD estimator to our baseline sample. The coefficient, $Treat_k$, captures the estimated effect of a fuel treatment located k distance bins (0.5 km each) from where the fire first encounters the treatment in a given direction. Column 1 reports estimates using the imputation approach of Borusyak et al. [25], column 2 follows Sun and Abraham [70], column 3 implements Callaway and Sant'Anna [71], and column 4 applies a standard two-way fixed effects estimator. Each regression includes fire-direction and distance-bin fixed effects, along with controls for environmental conditions, economic factors, and suppression efforts, as detailed in Table S4. We do not include controls in column 3 because the Callaway and Sant'Anna approach does not allow for time-varying controls. The regressions are estimated using the "didimputation" (column 1) [84], "fixest" (columns 2 & 4) [85], and "did" (column 3) [79] packages in R. Standard errors are clustered at the fire level.

Table S10: Spatial DiD Robustness Check - Alternative Treatment Thresholds

	Probability of Fire Spread				
	(1)	(2)	(3)	(4)	(5)
$Treat_0$	-0.075***	-0.158***	-0.135***	-0.063***	-0.026**
	(0.029)	(0.029)	(0.021)	(0.014)	(0.010)
$Treat_1$	-0.084**	-0.083***	-0.084***	-0.075***	-0.059***
	(0.041)	(0.027)	(0.022)	(0.016)	(0.017)
$Treat_2$	0.050	-0.016	-0.096***	-0.045*	-0.015
	(0.039)	(0.031)	(0.030)	(0.024)	(0.016)
$Treat_3$	-0.013	-0.034	-0.030	0.000	0.026
	(0.069)	(0.041)	(0.031)	(0.022)	(0.018)
$Treat_4$	-0.002	0.056**	0.018	0.012	0.099***
	(0.085)	(0.028)	(0.035)	(0.025)	(0.018)
Baseline	No	No	Yes	No	No
% Treated Threshold	100%	75%	50%	25%	>0%
Observations	73,280	71,624	69,174	63,709	49,788
R^2	0.44	0.44	0.45	0.47	0.51

*p < 0.10; **p < 0.05; ***p < 0.01.
The table presents results from five separate Spatial Difference-in-Differences (DiD) regressions estimating the impact of fuel treatments on the probability of fire spread, conditional on a plot not yet being extinguished. Each regression uses a different threshold for defining a treated plot, where a plot is considered treated if X% of its area or X% of the area of the plot directly in front of it (in the same direction but one distance bin closer to the origin) contains fuel treatment. Columns 1-5 report estimates for thresholds of 100%, 75%, 50%, 25%, and 0 percent. Our baseline estimates from use a threshold of 50%. The coefficient, $Treat_k$, captures the estimated effect of a fuel treatment located k distance bins (0.5 km each) from where the fire first encounters the treatment in a given direction. All samples include wildfires that intersect with USFS fuel treatments between 2017 and 2023, and observations treated more than 2.5 km away are excluded. Each regression includes fire-direction and distance-bin fixed effects, along with controls for environmental conditions, economic factors, and suppression efforts, as detailed in Table S4. Spatial DiD estimates are estimated using the imputation approach from [25] using the "didimputation" [84] package in R. Standard errors are clustered at the fire level.

Table S11: Spatial DiD Robustness Check - Changing the Event Window

	Probability of Fire Spread			
	(1)	(2)	(3)	(4)
$Treat_0$	-0.135***	-0.123***	-0.113***	-0.107***
	(0.021)	(0.021)	(0.022)	(0.022)
$Treat_1$	-0.084***	-0.072***	-0.058**	-0.052**
	(0.022)	(0.022)	(0.023)	(0.023)
$Treat_2$	-0.096***	-0.083***	-0.063**	-0.058*
	(0.030)	(0.030)	(0.032)	(0.032)
$Treat_3$	-0.030	-0.015	0.016	0.021
	(0.031)	(0.031)	(0.033)	(0.033)
$Treat_4$	0.018	0.036	0.070*	0.069*
	(0.035)	(0.037)	(0.040)	(0.040)
Baseline	Yes	No	No	No
Event Window	2.5 km	4 km	7 km	14 km
Observations	69,174	69,845	70,633	71,094
R^2	0.45	0.45	0.45	0.45

*p < 0.10; **p < 0.05; ***p < 0.01.

The table presents results from four separate Spatial Difference-in-Differences (DiD) regressions estimating the impact of fuel treatments on the probability of fire spread, conditional on a plot not yet being extinguished. Each regression is estimated on a different event window threshold. The coefficient, $Treat_k$, captures the estimated effect of a fuel treatment located k distance bins (0.5 km each) from where the fire first encounters the treatment in a given direction. All samples include wildfires that intersect with USFS fuel treatments between 2017 and 2023, and observations treated more than X km away are excluded based on the event window size. Columns 1-4 report estimates for event window sizes of 2.5, 4, 7, and 14 kilometers, where event window size 2.5 km is our baseline. Each regression includes fire-direction and distance-bin fixed effects, along with controls for environmental conditions, economic factors, and fire suppression efforts as detailed in Table S4. Spatial DiD estimates are estimated using the imputation approach from [25] using the "didimputation" [84] package in R. Standard errors are clustered at the fire level.