DISSERTATION

EVALUATING THE EFFICIENCY, EQUITY, AND EFFECTIVENESS OF WILDFIRE SUPPRESSION STRATEGY USING THE MICROECONOMIC TOOLKIT

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ABSTRACT

EVALUATING THE EFFICIENCY, EQUITY, AND EFFECTIVENESS OF WILDFIRE SUPPRESSION STRATEGY USING THE MICROECONOMIC TOOLKIT

Most economic research related to wildfires focuses on their impact on people and populations. In my dissertation, I use economic tools to evaluate the efficiency and equity of wildfire suppression strategy. In the first chapter, I investigate whether socioeconomic factors of a community (income, race, age, etc.) are correlated with allocations of suppression effort. I use spatial data on retardant drops from large airtankers (LATs) and demographic information from the Census Bureau to find that communities threatened by wildfire with fewer minority residents, but more low-income residents, are more likely to receive LAT drops. I then find that socioeconomic factors aren't correlated with the decision to use LATs in suppression after conditioning on biophysical factors like fuels and burn probability. In my second chapter, I study whether the media's attention to wildfire influences suppression strategy. I instrument for the effect of media attention using the incidence of catastrophic events that would distract the media to find that media scrutiny of a wildfire has no tangible effect on the decision to use aviation on a fire. Finally, most economic research on wildfire suppression strategy has focused on the costs; little exists on its benefits. I use causal inference methods leveraging satellite data on wildfire growth and intensity, along with the spatial data on aerial suppression effort mentioned previously, to find that large airtankers are effective at limiting the physical extent of wildfire's spread, reducing the intensity of flames as it grows, and slows its spread.

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DEDICATION

I would like to dedicate this work to my amazing wife for her unwavering support. This work surely would not have been accomplished, without Melissa.

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Chapter 1

Introduction

Wildfire imposes a significant externality on society, directly and indirectly (Bayham, Yoder, et al. 2022). The adverse effects of that externality are felt strongest by local communities through home/structure loss (Buechi et al. 2021) or other damages felt by local economies (Walls and Wibbenmeyer 2023; Milne et al. 2014). In 2020, wildfires destroyed 17,904 homes/structures (F. S. USFS 2020b) a stark increase from the 245 destroyed in 2005 (F. S. USFS 2021). Damages from wildfire can also be felt by communities not directly threatened by a wildfire through smoke exposure (Lepeule et al. 2012).

Land managers have an opportunity to allocate resources that produce "effort" to reduce the damages borne by the wildfire being suppressed. Incident management teams must make high-stakes decisions about resource deployment, often in the face of limited availability and competing demands. The competition for these critical resources has intensified with the increased prevalence of large wildfires occurring simultaneously (McGinnis et al. 2023), raising important questions about how they are allocated and managed. The increasing frequency and severity of wildfires, driven by factors such as climate change and urban expansion, have made wildfire suppression a critical focus of resource management and economic analysis.

Despite the crucial role that these decisions play in wildfire management, there remain significant gaps in the research on wildfire resource allocations. Existing studies have largely focused on the costs of suppression strategies, with less attention paid to their benefits or to the equity of resource distribution. This dissertation addresses this gap by investigating the economic principles of equity, efficiency, and effectiveness in the context of wildfire suppression, providing a more comprehensive understanding of how these resources are allocated and the broader implications for communities.

There are many dimensions to consider for any resource manager providing a public good. Savas 1978 proposes three critical lenses to evaluate any resource allocation: equity, efficiency, and effectiveness. It is through these three measures of performance that we can learn more about the totality of costs and benefits borne from a public good for all relevant stakeholders; especially for spatially allocated resources. This framework was developed for the provision of a public good used in emergency response, ambulances (Savas 1969; Savas 1978). I extend the work of Savas by evaluating these three lenses for a different public good used in emergency response; large airtankers.

It is essential that we understand these three performance standards for wildfire suppression resource allocations. Savas's framework highlights the importance of balancing efficiency (maximizing resource use), equity (ensuring fair access to resources), and effectiveness (achieving desired outcomes) in the high-pressure situations created by wildfire. By assessing these three lenses, we can ensure that wildfire suppression strategies are not only fair and just but also strategically sound and impactful. Understanding the balance between these metrics allows us to allocate resources in a way that maximizes societal benefit while minimizing costs and harm.

It's important that we understand the equity of suppression resource allocations as wildfire risk rapidly increases as more people choose to reside in the wildland urban interface (WUI) (Radeloff, Helmers, Kramer, Mockrin, Alexandre, Bar-Massada, Butsic, Hawbaker, Martinuzzi, Syphard, et al. 2018). Are resources allocated purely as a function of expected damages, or are there communities that are less likely to receive suppression effort? Do we spend more money on suppression in certain types of communities? Having a grasp on equity will give us a sense of how the economic benefits and costs of these resources are shared amongst relevant stakeholders.

Research on resource equity highlights the critical need to also understand the efficiency of wildfire suppression strategies, especially as the frequency of large wildfires continues to rise. As more communities face the growing threat of wildfires, particularly in the wildland-urban interface (WUI), it is essential to examine whether resources are allocated fairly and effectively. The increasing scarcity of suppression resources (Belval, Stonesifer, and Calkin 2020b) further underscores the importance of ensuring that every dollar spent not only reaches those who need it most, but also does so in the most efficient manner possible.

We wouldn't be concerned with the equity or efficiency of a resource if it were ineffective at achieving its intended goal. The effectiveness of a suppression strategy is the foundation upon which equity and efficiency rest. We must first parameterize the suppression effectiveness of a resource before we can analyze its efficiency through a cost-benefit framework, or claim that it is equitably (or inequitably) allocated.

This dissertation will focus on the role of large airtankers (LATs), a resource used for aerial firefighting, across three distinct studies, each examining their use through the lenses of equity, efficiency, and effectiveness. These studies aim to provide a comprehensive evaluation of how this critical and costly suppression resource is deployed, managed, and its broader implications for wildfire management. By thoroughly understanding how and where LATs are most effective, we can better align their deployment with the principles of equity and efficiency, ensuring that these valuable resources are used in ways that maximize both societal benefits and the protection of vulnerable communities. In the following subsections, I provide more background on (i) how resources are allocated in response to wildfire and (ii) aerial firefighting.

1.0.1 Background on Wildfire Response

Wildfire response is a complex endeavor that requires coordination across several agencies in a rapidly changing environment. Incident managers or teams develop strategies and deploy firefighters to reduce the impact of wildfire on people, property, and other valued assets. These strategies may differ on an incident-by-incident basis, or even on a team-by-team basis, with priorities ranging from limiting the fire's spread, reducing the fire intensity, point protection of values at risk, or more (F. S. USFS 2020a). These dynamic incident-level strategies require ongoing management of resource assignments. There has been increased competition over these resources that carry out a suppression strategy given the increased prevalence of large wildfires burning simultaneously (McGinnis et al. 2023).

Over the course of the fire season, suppression resources are managed at multi-agency dispatching centers at local, geographic, and national levels. When there are no binding resource constraints, requests by incident management for suppression resources are generally obliged. When there are binding resource constraints, then the requests are prioritized by multi-agency coordinating groups (Belval, K. C. Short, et al. 2022). These coordinating groups then decide which incidents to dispatch each individual resource; aircraft equipped to fight fire, wildland fire engines, hand crews, etc. Resource assignments at the geographic level are made as a function of the resource type requested at the incident level, relative resource scarcity across the region, and other regional priorities/considerations[1] (Hand, Katuwal, et al. 2017).

There is a wide range of resources available to suppress wildfire, each with its own set of strengths and weaknesses. These resources can be classified as either aerial firefighting or ground-based suppression. Ground-based wildfire suppression is labor-intensive (Moseley, Sandoval, and Davis 2014), often digging containment line around a wildfire's perimeter or "mopping up" the interior of a perimeter (checking for hot spots) after a burn. Aerial firefighting is more capital-intensive. The spatial coordination of labor and capital across a wildfire's landscape adds another layer of complexity to a suppression strategy.

Resources used for wildfire suppression can also be classified along another dimension as well; direct or indirect wildfire engagement (Duff and Tolhurst 2015). Resources that directly engage with the wildfire will suppress its growth through reducing the intensity of its flames. These will be ground resources like fire engines or aviation like helicopters or scoopers. Resources that indirectly engage with the wildfire will produce containment line that aims to limit the physical capacity of the wildfire to spread. This will include ground resources like hand crews or dozers, or aviation like LATs.

After a resource has been dispatched to a particular incident, the incident commander (henceforth referred to as the "IC") or the incident management team (IMT)[2] decides how that resource

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[1] These coordinating groups release priority matrices which they use to determine resource assignments when they are faced with scarce resources (formally defined as preparedness levels 4 and 5). Examples of these priority matrices can be seen for the state of California and the Rocky Mountain region (Forest Service, Dept of Forestry and Fire Protection, et al. 2022; Forest Service 2020).

[2] To be specific, on more complex incidents (type 3/2/1) it is the ops section chief of the IMT that assigns tasks to for each individual resource. On less complex incidents (5/4), resource assignments are made by the IC.

will be deployed at the fire level. Theoretically, IC/IMTs make decisions based on assumptions about the marginal effectiveness of placing a resource in a location (Bayham and Yoder 2020). Decisions over the location of suppression effort allocations can be of great consequence, as there are opportunity costs to each choice.

Wildfire can cover quite significant geographic range, meaning that candidate locations to dispatch a resource to may cover a large extent[3]. A fire engine stationed on the northern perimeter of a wildfire could be unavailable to perform any tasks at the southern edge of the wildfire. Similarly, an IC or IMT[4] assigning a LAT to deliver fire retardant to a particular location on a fire could potentially come with comparable consequences, although on a shorter temporal scale.

The spatial location of wildfire suppression effort will be a function of several different choices, each by a different stakeholder. Two of the dimensions I evaluate resource allocations under, equity and effectiveness, require analysis of spatial patterns. It is worth noting that it is not just the IC's or IMT's that have influence on the exact placement of a suppression input on a wildfire, especially for LATs. Depending on incident size, operations personnel (OSC/DIVS) could have an influence on suppression resource placements. Additionally, aerial supervision (ATGS/ASM) holds authority in the placement of firefighting aviation resources on a wildfire. Once deployed on a wildfire, pilots, squad bosses, and engine captains have the ability to determine the final placement of suppression inputs like containment lines, based on factors such as weather conditions and other resource activity. Because of this nuanced system, we can't solely attribute the exact geographic placement of a suppression resource to individuals in an incident's management team. Instead, they are a function of several different agencies, teams, and individuals.

1.0.2 Background on Aerial Firefighting

Aviation has aided in controlling wildfire for over a century now. The first sustained use of aviation as a resource in firefighting began in 1919 (Dubay 2015), when the USFS began using

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[3] The 2021 Dixie fire burned an area larger than the state of Rhode Island (F. S. USFS 2021).

[4] On more complex and long-term incidents, the responsibility of placing aircraft on their roles goes to the Air Tactical Group Supervistors (air attack).

airplanes as a fire detection tool. In the 1920's, the USFS began experimenting with dropping water from airplanes, but found little success[5]. In the subsequent decades, aviation resources were assigned to wildfires primarily for transportation purposes, dropping supplies and smokejumpers into close range of the active fire. What is now seen as the first successful "free-flowing water airdrop" did not occur until 1955 on the Mendocino National Forest in California (Dubay 2015). This sparked wider interest in forest stakeholders to research ways that we could expand aviation use in the direct attack of wildland fire, including the use of military aircraft.

Aviation resources can fill multiple roles when it comes to fire suppression: reducing fire intensity, delaying fire spread, supporting ignition operations, protecting values at risk, halting the fire's advance, or extinguishing fires (F. S. USFS 2020a). Today, while there are a wide variety of models of aircraft used in fire suppression efforts, they are mostly broken down into three categories: helicopters, scoopers, and airtankers. Airtankers are broken up into three categories; single engine airtankers (SEATs), large airtankers (LATs), and very large airtankers (VLATs); and are primarily used to halt the fire's advance due with fire retardant they drop from their hull. Scooper and helicopter use is more focused on using water to halt a fire's advance due to their relatively quick refuel time and travel speed.

From 2013 to 2020, the USDA conducted the Aerial Firefighting Use and Effectiveness Report (F. S. USFS 2020a). This report focused on the operational effectiveness of aviation use on wildfires and not direct suppression effectiveness, primarily due to data reasons (Thompson, Calkin, Herynk, et al. 2012). They found that helicopters and scoopers achieved the greatest probability of success at providing ignition support (96-100%) and reducing fire intensity (80-89%), while air tankers are relatively more effective at protecting values at risk (78-87%). The study also found all aviation resources to be relatively more effective at initial attack than at extended wildfire management objectives. Most federal policy dictates that airtanker use should emphasize initial attack of wildfires, despite research showing most use on extended attack (Calkin, Stonesifer, et al. 2014; Thompson, Calkin, Herynk, et al. 2012).

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[5] The most notable of these experiments was dropping wooden beer kegs on the active fire.

Past research on the effectiveness of aerial firefighting focused on what characteristics of the wildfire maximize its suppression success. Plucinski 2012 finds that (i) the size of the fire at initial response and (ii) time in between detection and first containment output are two significant determinants of aerial containment success. Others show that the more information that is known about a wildfire at the time of initial attack, the higher the likelihood is of successful containment using LATs (Wheatley et al. 2022). Aerial firefighting techniques are often used in concert with fuel breaks[6]; the size and shape of those fuel breaks is an important factor in aerial firefighting success (Restas 2023).

Aerial firefighting is not only expensive (Restás 2014), it is also dangerous. 52% of all wildland firefighting fatalities from 2000 to 2012 were from aviation-related causes (Stonesifer, Calkin, Thompson, and Kaiden 2014). After a couple of high-profile plane crashes during the active suppression of wildfires, both of which led to fatalities, the Forest Service pivoted away from owning its own fleet of aircraft. Today, this resource is managed by private firms and the use of the aircraft is contracted out to the federal government either on a CWN (Call-When-Needed) or EXU (Exclusive Use) contract (Belval, Stonesifer, and Calkin 2020b).

The use of aviation to suppress active wildfire has received scrutiny from the media and public, given its high costs and relative danger (Restas 2023). Beyond research into aerial firefighting's suppression effectiveness, there are high levels of interest in operationalizing a system to efficiently, effectively, and safely fight fire. Stonesifer, Calkin, Thompson, and Kaiden 2014 propose an "Aviation Exposure Index" to capture the hazard level of an aerial mission. They build on that further in Stonesifer, Calkin, Thompson, and Belval 2021 by fully developing a framework to weigh the risk of the flight against its potential benefit. Incorporating equity, effectiveness, and efficiency into this framework is essential to ensure that aerial firefighting operations not only maximize safety and cost-effectiveness but also distribute resources fairly and deliver the best possible outcomes for all communities affected by wildfire.

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[6] Fuel breaks can be natural or man-made. Ones that are man-made could have been created as a part of a fuels reduction project, or as a part of a suppression strategy.

Chapter 2

Equitable Response to Natural Disasters: Evidence from Aviation Use During Wildfire

Abstract:

Climate change is driving increasingly frequent and destructive wildfires. While the burden of wildfires is likely to fall on those in the most fire-prone areas, the response to wildfire is a choice determined by agencies responsible for wildfire management (USFS, etc.). Aviation resources, including airtankers and helicopters, are the most expensive resource used to respond to wildfire. However, little is known about whether the distribution of aircraft use is equitable. Using detailed data on when and where aerial resources for wildfire suppression are used, we find no strong evidence that aviation use is inequitable within or near wildfire perimeters.

2.1 Introduction

Over the last several decades, wildfires have rapidly grown in severity and increased in frequency throughout the western United States (Abatzoglou and Williams 2016; Williams et al. 2019). Since 1985, the number of acres consumed by wildfire annually has nearly quadrupled (Burke, Driscoll, et al. 2021), in part due to an average annual increase of seven large wildfires per year (Dennison et al. 2014). Expanded development into the wildland-urban interface (WUI) is making wildfire management more complex (Burke, Driscoll, et al. 2021). From 2000 to 2020, the number of census tracts exposed to wildfire in California doubled, corresponding to an almost doubling in the number of people living in fire-affected census tracts (Masri, Scaduto, et al. 2021). While recent research suggests that populations exposed to wildfire are older, whiter, and have higher income (Wibbenmeyer and Robertson 2022), less is known about the equity of wildfire response.

The objective of this study is to evaluate whether wildfire response effort is equitably allocated. Using data on wildfire perimeters and large airtanker (LAT) deployments, we evaluate whether there are systematic differences in aerial firefighting resource allocations along racial, ethnic, or income lines. We first analyze summary statistics of census tracts to assess whether any differences exist between communities that do and do not receive wildfire aviation resources during an active incident. Then, we determine whether socioeconomic features of a community are correlated with the amount of aviation use after controlling for biophysical factors related to wildfire spread/growth.

Environmental justice is defined by the EPA as "the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income, with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies" (EPA 2022). It has been an important area of research ever since the illegal dumping of toxic chemicals in Warren County, NC in 1982. In January 2021, President Joe Biden signed an executive order titled the "Justice 40 Initiative" into effect, stating that 40% of federal funds allocated for combating climate change and moving toward clean energy must go toward "environmentally disadvantaged" communities. Following the implementation of this executive order, a significant amount of research has focused on identifying which communities are affected by climate change, overburdened with pollution, or overexposed to natural disasters (Masri, LeBrón, et al. 2021; Smith and Wodajo 2022; Mullen et al. 2022; Lathwal, Vaishnav, and Morgan 2022).

For decades, the environmental justice literature has documented disparities between disadvantaged communities and their counterparts. Miranda et al. 2011 find that clean air laws do not reduce the burden of air pollution across disadvantaged communities. Several studies find that waste facilities are disproportionately placed in communities of ethnic minorities (Bullard 1983; Martuzzi, Mitis, and Forastiere 2010). Harrison 2011 find that socially vulnerable groups are overexposed to the effects of "pesticide drift." Banzhaf, Ma, and Timmins 2019 suggest several mechanisms that contribute to disproportionate exposure in disadvantaged communities, including politically motivated decision-making, the siting of hazardous facilities in these areas, and low-income communities "coming to the nuisance" due to a lower willingness to pay for environmental amenities[7].

The environmental justice literature also documents differential exposure to natural disaster risk along socio-economic dimensions. A significant amount of this research identifies which groups have homes that are disproportionately exposed to flood risk directly (Bakkensen and Ma 2020; Chakraborty, Collins, and Grineski 2019; Walker and Burningham 2011) and indirectly (Morse 2008). One particular challenge of determining this impact is disentangling the role flood risk has in influencing housing decisions, from the desire for coastal amenities. Bullard and Wright 2009 use the aftermath of Hurricane Katrina in New Orleans, LA and Mississippi to determine if there are environmental justice concerns in disaster response for certain populations, conditional on exposure. They find that neighborhoods with a lower socio-economic status are less likely to receive infrastructure improvements following the disaster, while people of color and low-income populations spend more time in temporary housing.

Wildfire is a unique natural disaster in that effort can be invested to reduce damages prior to, during, and after an event's occurrence, meaning there are several different points when the risk of wildfire damages can be mitigated. The distribution of exposure to wildfire risk[8] at these different points in time (relative to a wildfire ignition) is an important topic of research in environmental justice, with parallels to work on the distribution of flood risk (Stetler, Venn, and Calkin 2010). Masri, Scaduto, et al. 2021 use the occurrences of wildfire in California from 2000 to 2020 and find that the population of census tracts most affected by wildfire have a greater share of low-income residents, but a lower share of minority residents. Wibbenmeyer and Robertson 2022 use property-level data to find that the distributional incidence of wildfire hazard is disproportionately placed upon high-income, white, and older individuals.

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[7] See (Depro, Timmins, and O'Neil 2015) for an even more robust explanation of the "coming to the nuisance" hypothesis.

[8] By "exposure to wildfire risk", we refer to both (i) the ambient threat of wildfire and (ii) the negative externalities that come with wildfire risk, like smoke exposure.

In terms of pre-ignition risk mitigation, Anderson, Plantinga, and Wibbenmeyer 2022 use the exogenous nature of wildfire ignition points as a natural experiment, finding that there is an unequal distribution of fuel reductions projects based on the proximity of a recent ignition to a census tract, an effect that is more profound for communities with a higher socioeconomic status. Johnson Gaither et al. 2019 and Jones and Berrens 2021 find evidence that there could be inequality in the social distribution of the negative spillover effects of risk mitigation; African-American populations in Georgia are disproportionately subjected to PM2.5 from prescribed burns. Adams and S. Charnley 2018 develop a framework for testing whether hazardous fuel reduction projects are undertaken with environmental justice in mind.

We are not the first to research the social equity of active wildfire suppression effort; Wibbenmeyer, Plantinga, and Walsh 2022 study the determinants of wildfire suppression effort and the spatial distribution of these resources; they find that wildfire is more likely to stop spreading as it approaches homes, an effect that is greater for homes of higher value. In contrast to Wibbenmeyer, Plantinga, and Walsh 2022, who infer suppression effort, we use observable aviation drops.

Resource decisions can vary greatly from incident to incident, even after conditioning on biophysical factors like terrain and vegetative fuels. There is evidence of non-biophysical, or "human", factors influencing suppression decisions. Donovan, Prestemon, and K. Gebert 2011 find that media attention on a wildfire is correlated with a rise in suppression costs. Suppression costs on wildfires have been shown to significantly vary based on leadership, all else equal (Hand, Katuwal, et al. 2017). Specifically, the role of risk aversion (Wibbenmeyer, Hand, et al. 2013) in incident manager(s) decisions is an important determinant of resource allocations. However, we know very little about the role demographic or socioeconomic features of an affected community have in wildfire resource decisions, or if there is heterogeneity in suppression strategies of wildfires that threaten disadvantaged communities.

Wildfire response decisions have a tendency to be expedient and reactionary. Preparation for fire allows time for deliberation and careful planning, but response to an active incident is rushed. Suppression decisions are often made with incomplete information (Thompson, Calkin, Finney, et al. 2011). Initiatives like Justice 40 are focused on decisions to allocate resources based on a deliberative planning process, rather than an emergency response situation, with stated goals to “facilitate planning and implementation of key Federal actions to reduce climate pollution”. Nonetheless, understanding inequities in wildfire suppression during an active incident may help incident managers plan response strategies that reduce future inequities.

The ability to apply effort to reduce expected damages when directly (or indirectly) facing the threat of wildfire aids our research. While most environmental justice researchers focus on the distribution of effort to reduce the ambient risk of natural disasters, we are able to determine if there are any patterns in the allocation of resources to mitigate the risk of an *active* disaster.

We find evidence to support our hypothesis that the census tracts that receive aviation support tend to be older, less ethnically diverse, and have lower income. We also find that, after conditioning on factors related to the complexity of wildfire suppression campaign, demographic factors have no effect on the allocation of LATs.

2.2 Methods

2.2.1 Conceptual Framework

It is critical to explicitly define the terms "justice" or "equity" in environmental justice research topics, as there is not one unifying definition of these terms in the economics literature. This research focuses on the distributional equity of fire suppression resources. We adopt a similar definition of equity as Li 2023, revised for the allocation of fire suppression resources: an equitable allocation of fire suppression effort would mean that each community receives firefighting resources according to its expected wildfire damages.

Resource allocations can be equitable on two different temporal dimensions: *ex-ante* or *ex-post*. Research on the *ex-post* equity of a resource allocation(s) focuses on how outcomes were distributed among the recipients of those allocations (Leclerc, McLay, and Mayorga 2012). We focus on the *ex-ante* equity in this research, as we are concerned with how the resources were allocated prior to their production of suppression effort[9], similar to other research on the allocation of wildfire risk/damages (Wibbenmeyer, Plantinga, and Walsh 2022; Adams and S. Charnley 2018).

There are other classifications of environmental justice beyond the temporal point of analysis (*ex-ante* or *ex-post*). A large share of environmental justice research evaluates either the *procedural* or *distributive* justice of resource allocations (Leclerc, McLay, and Mayorga 2012). Procedural justice refers to the participatory and inclusive decision-making processes involved with allocated resources, while distributive justice refers to the allocation of resource costs and benefits for all social groups (Schlosberg 2013). In this research, we focus on the distributive justice of firefighting resource decisions, not the procedural justice[10], as our concern regards the socio-spatial patterns of where suppression effort is allocated (Calderón-Argelich et al. 2021).

Conceptually, we model the *ex-ante* equity in the distribution of firefighting resources as a function of a larger objective by land managers to minimize wildfire damages to afflicted communities. That objective is constrained by a limited set of resources available to an incident manager, since distributive equity is concerned with both the recipient's needs and resource availability (Hoffman and Davidson 2003). We write the decision-maker's problem as,

$$\text{Min} \sum_c D_c \quad s.t. \quad \bar{E} \geq \sum_c E_c \tag{2.1}$$

D_c represents the economic damages from wildfire to community c. Where -

$$D_c = \Psi(F_c, w_c, E_c, \epsilon) \tag{2.2}$$

Wildfire damages are primarily a function of a census tract's biophysical susceptibility to wildfire, defined as F_c. This will contain information like the type and concentration of vegetative fuels, topography, or population density. Because we are abstracting away from time, F_c will also

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[9] An exploration into the *ex-post* equity of large airtanker (LAT) allocations might focus on where they *successfully* controlled a wildfire's spread, not just where they placed retardant drops.

[10] Refer to Johnson Gaither et al. 2019 or Jones and Berrens 2021 for examples of research on the procedural justice of wildfire risk allocation. They find that certain social groups are overexposed to smoke as a byproduct of hazardous fuel reduction projects.

capture other relevant information like latent risk to firefighters. w_c is a vector of exogenous factors that determine a potential wildfire's expected severity in community c. w_c will also measure the frequency of wildfire spread in community c over our sample period, an important consideration in a cross-sectional analysis that abstracts away from time[11]. ϵ captures unobservable variation in wildfire damages as a function of land manager decisions.

Wildfire incident managers can use firefighting resources to reduce damages to people and property through the production of suppression effort. In the ideal world, an incident manager chooses a level of suppression effort that solves Equation 1. The solution to that decision will be defined as -

$$\mathbf{E}_c{}^* = \Phi(\mathbf{F}_c, \mathbf{w}_c, \mu) \tag{2.3}$$

They will allocate $E_c{}^*$ to community c. The incident manager does not only choose the type and quantity of firefighting resources to allocate to c; they also select a level of effort for those resources to produce[12]. μ captures unobservable variation in wildfire damages as a function of land manager decisions.

In the context of aerial firefighting resource allocations, we are able to assume $\bar{E}$ (Equation 1) as exogenous because we are focusing on the allocation of aerial firefighting resources. It is not uncommon for large airtankers (LATs) to aid in wildfire suppression on multiple fires in one day. This means that incident managers are not going to be constrained by the number of aircraft dispatched to a particular wildfire but rather by how many aircraft are available in their geographic region. Therefore, we can assume $\bar{E}$ to be exogenous as it will be a function of how many other fires there are competing for their use at the regional and national level (Belval, K. C. Short, et al. 2022).

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[11] We choose to abstract away from time as the demographic factors that are our main variable of interest don't vary over our sample period.

[12] Ex: How much containment line will a hand crew dig? How many buckets of water will a helicopter release?

There are several pathways for demographic factors, like race or income, to influence suppression effort allocations to a community. Mobilization guides, including the Rocky Mountain region's (Forest Service 2020), cite economic values, the potential for media interest, or other external interests as reasons to prioritize dispatching a resource to an incident. Other community features, like income, correlate with wildfire preparedness, allowing for a higher probability of suppression success. Since incident management often prioritizes the probability of success when making suppression decisions, the likelihood of a community receiving a unit of suppression effort could be correlated with socioeconomic conditions (like income) through this channel. Other socioeconomic factors of a community, such as race or income, may be correlated with the presence of environmental amenities like public land or vegetative green space.

Our goal is to test the hypothesis that socioeconomic characteristics of a community are a factor in wildfire resource allocations. We define those socioeconomic characteristics as S_c. If resource allocations are a function of factors like race or income, then we would observe the following -

$$E_c = \Phi(F_c, w_c, S_c, \mu) \tag{2.4}$$

Identifying the community that is the intended recipient of a unit of suppression effort is a challenge. Incident managers don't always have an explicit community c in mind when they are assigning firefighting tasks. Some resources suppress the spread of fire by generating containment lines, like hand crews, dozers, or LATs. Containment can be generated to slow the spread of a wildfire directly, or applied in defense of structures. In a post-hoc analysis of equity, we are left uncertain (i) if a unit of suppression effort was defending a particular piece of land and (ii) if so, its proximity to that piece of land. Therefore, the most accurate way to determine if suppression effort was provided to a particular community is to determine if a suppression input was allocated inside of its borders.

Theoretically, the optimal solution of how much suppression effort to allocate a community, ${E_c}^*$, should be a function of the same factors that define how prone it is to damage; F_c and w_c. Incident managers will evaluate fire spread projections to determine spatial points of emphasis when they are determining where to allocate suppression effort (Thompson, C. D. O'Connor, et al. 2022). F_c contains information that is also an essential input to those spread projections, like the topography, fuel type/concentration, and burn probability. w_c informs us on the people, homes, and structures threatened by wildfire, an important factor in decisions on how much suppression effort to allocate. We should expect these factors to be highly correlated with firefighting resource assignments. In theory, if two identical communities are threatened by the same advancing wildfire, more suppression effort would be applied to the community with greater wildfire hazard potential, assuming *ceteris paribus*.

Unlike these biophysical factors, we should theoretically not expect the demographics of a community to be a consideration in the optimal resource allocation ${E_c}^*$. Equation 5 will capture whether wildfire resource allocations are a function of the socioeconomic characteristics of a community. Other research on the environmental justice of wildfire hazard distribution has focused on determining if socioeconomic characteristics of a community are correlated with damages (Wibbenmeyer and Robertson 2022; Masri, Scaduto, et al. 2021). Referring to Equation 2, they determine if D_c is correlated with S_c. Our research is unique by analyzing if there is a statistical correlation between E_c and S_c.

Equity and equality are distinct concepts in the literature on resource allocation (Valipour et al. 2024). An allocation of firefighting resources that prioritizes *equality* will distribute the same amount of effort to each threatened community, regardless of its vulnerability to wildfire damages. An *equitable* allocation considers vulnerability. Equations 1 through 5 contextualize how resource decisions are made on a community-by-community basis; they do not explicitly measure whether a resource decision is unjust. It is impossible to explicitly prove a resource allocation is "equitable". Instead, we can measure the degree of *inequity* that is generated from the distribution of firefighting resources.

Hoover's concentration index gives a sense for how we are thinking about measuring the fairness of firefighting resource allocations across different communities. Mulligan 1991 uses this index to measure the inequity in facility siting decisions as a function of the travel distances and the relative population sizes of the groups using the facility. If land managers wanted to estimate the inequity of a potential allocation of firefighting effort across communities threatened by a wildfire, they could use a measure modeled after the HCI (Hoover 1936) in the following way -

$$I = \frac{1}{N}\sum_{c} \frac{E_c}{\sum\limits_{c} E_c} - \frac{{E_c}^*}{\sum\limits_{c} {E_c}^*} \tag{2.5}$$

Just as in Equations 1 - 5, E_c represents the suppression effort that an incident manager chose to allocate to community c. The denominator of the first term, $\sum_c E_c$, represents how much total suppression effort was allocated across all afflicted communities. ${E_c}^*$ again represents the optimal resource allocation to community c as a function of its expected wildfire damages. ${E_c}^*$ reflects the suppression needs of community c, excluding any human factors in decision-making, such as biases, risk aversion, or institutional considerations. $\sum_c {E_c}^*$ is the aggregate suppression need of all communities threatened by a wildfire. According to Equation 6, if every community received the exact proportion of available firefighting resources relative to their need and the needs of other communities, then there would be no inequity. That measure of inequity rises the more we deviate from the idealized situation.

If the race, poverty, or other social characteristics of a community were negatively correlated with E_c, that would correspond to more inequity. There is no channel for socioeconomic factors to affect the idealized wildfire response ${E_c}^*$. Those factors could be correlated with changes in the actualized response E_c if S_c is nonzero in Equation 5. If that is the case, the disparity between the actualized and idealized wildfire response could only grow, leading to a larger measure of inequity in Equation 5.

We defined an equitable firefighting allocation as the distribution of fire suppression effort to each community so that they receive resources according to their sensitivity to wildfire damages. When evaluating the equity of resource allocations, we should not consider communities that are not directly[13] affected by wildfire. It is a challenge to identify the communities threatened by a

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[13] Due to wildfire smoke's health and economic impacts (Liu et al. 2015), a wider range of communities may be indirectly affected by a wildfire, but aren't actively considered in resource allocations.

wildfire without contemporaneous knowledge of its spread behavior. It is impossible for incident managers to know precisely what direction a fire will spread, at what speed or intensity, or how much longer it will last. Therefore, in a post-hoc analysis, the only communities we can know with certainty that were indeed subject to resource deployments are the ones that overlap with a wildfire's final area. It would not be appropriate to compare communities that received damages to ones that didn't. "Sensitivity to wildfire damages" is a precondition to needing suppression effort in a community; we can only be certain of that sensitivity for the communities that burned.

In this research, we first investigate if there is any ex-ante inequality in the distribution of suppression effort through a descriptive analysis of LAT allocations across different socioeconomic groups. We then focus on the equity of these allocations by estimating their correlation with socioeconomic factors after conditioning on determinants of wildfire risk. In the following subsection, we describe how we assembled our data to conduct this unconditional and conditional analyses of the equality and equity of wildfire resource allocations.

2.2.2 Data

We build a unique dataset for our analysis leveraging several data sources. We start with the Justice 40 data on environmentally disadvantaged census tracts and the indicators contributing to those designations. We use spatial data on final wildfire perimeters from Monitoring Trends in Burn Severity (MTBS) to identify which census tracts have been exposed to wildfire. Data from Additional Telemetry Units (ATU) on firefighting aircraft is used to determine which communities received aviation effort during our sample period. We gather socioeconomic and health indicators from EJScreen. We also obtain more detailed socioeconomic data at the tract level from the Census Bureau, including the share of a census tract's residents that belong to specific ethnic groups. We obtain raster data from the Forest Service on two important spatial determinants of wildfire resource decisions, burn probability and wildfire hazard potential, and integrate that into our data. Additional spatial determinants of wildfire resource allocations include fuel types and concentrations, terrain/elevation, and population density. Raster data on those factors are obtained from

Landfire, USGS, and Landscan. Geospatial information on public land management from PAD-US is also included in our data.

We used the fire perimeters available from Monitoring Trends in Burn Severity (MTBS) to determine which communities were fire-affected. We elect to only keep the wildfires in the MTBS data from 2017 to 2020 that occurred in the western Geographic Area Coordination Centers (GACCs)[14]. The data hosted by MTBS come from a multi-agency collaboration to map the severity and extent of wildfires in the United States dating back to 1984. MTBS is an initiative coordinated through multiple land management agencies that uses satellite imagery from the 30-m time series LANDSAT images to map the burned area of all fires over 1000 acres. After trimming our sample only to fires in our temporal and spatial window, we are left with 828 wildfires for determining which communities have been exposed to wildfire.

We focus on the distribution of federally provided large airtankers (LATs) as our measure of wildfire suppression effort. First, aviation resources are among the most costly forms of suppression effort both in terms of monetary expense (Stonesifer, Calkin, Thompson, and Belval 2021) and risk to firefighter safety[15] (Butler, M. B. O'Connor, and Lincoln 2015). Second, flight and drop data are consistently tracked with automated GPS units that provide accurate information on precisely when and where suppression effort occurs. Unfortunately, there is no comparable data on ground resources[16]. The data we obtain on aviation use is provided by the U.S. Forest Service (USFS) and details every aerial drop of fire retardant made by a large airtanker (LAT). These data are both temporally and spatially explicit; the geographic coordinates of each drop offer crucial information for analyzing the allocation of suppression effort. The final reason we focus on the allocation of LATs is that they are often used to amplify the effect of containment lines created

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[14] To be specific, census tracts in our analysis only come from the states of Arizona, California, Colorado, Idaho, Kansas, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oklahoma, Oregon, South Dakota, Utah, Washington, and Wyoming. We believe that this provides us with the most accurate and up-to-date picture of the social equity regarding wildfire suppression in the United States.

[15] According to Butler, M. B. O'Connor, and Lincoln 2015, over a quarter of all firefighter fatalities from 2000 to 2013 involved aircraft.

[16] There is spatial data on ground resource allocations, like dozers, but the data has questionable quality and consistency (Katuwal, Calkin, and Hand 2016a).

using other suppression resources (Simpson et al. 2022). Therefore, LAT allocations could be a proxy for other suppression resource allocations in a community. After trimming our sample to only aviation effort applied to an active wildfire, we have a sample of 30,598 drops occurring from 2017 to 2020 across seventeen states[17]. Figure 2.1 contains a map of aviation use throughout our sample years and across our region of analysis.

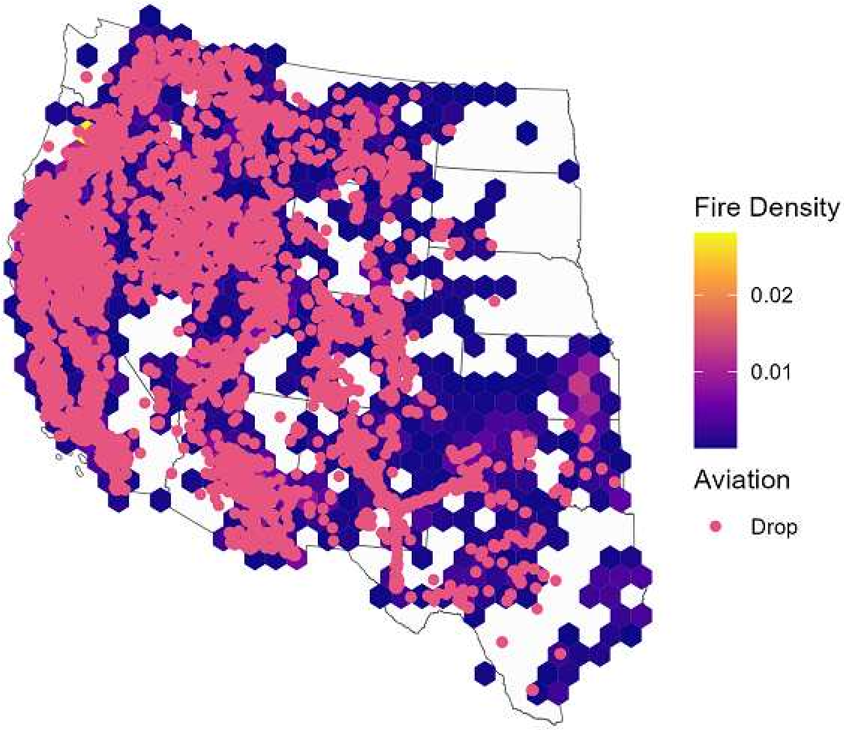

Figure 2.1: Map of aviation use and density of MTBS wildfire perimeters

We incorporate data into our fire-affected census tracts on social and environmental vulnerability released by the federal government. Following President Biden issuing Executive Order 14008, the Council on Environmental Quality developed a screening tool to identify environmentally disadvantaged communities (White House 2022). The screening tool provides a central repository for

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[17] Aviation resources operated from non-federal firefighting agencies, such as CALFIRE, are not included in the dataset.

environmental and socioeconomic data and identifies environmentally disadvantaged census tracts; communities which have been marginalized, under-served, and overburdened by pollution[18]. We use these data from the Justice 40 screening tool to identify which census tracts in our analysis have been broadly deemed “disadvantaged”, then see if these communities are also less likely to receive wildfire suppression resources.

We supplement these data with the EPA’s EJScreen mapping tool to gain information about the share of residents in each census tract that are minority, elderly, or below the poverty line (EPA 2022). EJScreen uses up-to-date mapping techniques to ensure that the EPA is keeping up with its responsibilities of protecting public health and the environment across all populations. We use EJScreen to gain information on how tracts might differ on the previously mentioned socioeconomic factors. Most EJScreen data sources originate from publicly available sources, like the U.S. Census Bureau. Additional demographic information is also included in our data from the Census, including the resident share of a census tract belonging to certain ethnic groups.

Our analysis leverages several geospatial data sources to account for the role biophysical factors could have in any resource allocation. We use burn probability from the USFS to define the likelihood of a wildfire ignition (K. Short et al. 2016) in a census tract. The "burn probability" layer uses simulations of tens of thousands of hypothetical fire seasons based on varying weather, fire growth, and suppression strategy scenarios and spatially resolved as a 270m grid. This information allows us to condition our results on the likelihood of a census tract observing a wildfire ignition in the first place, likely an important factor in resource allocations. However, burn probability is not the only direct determinant of a tract’s likelihood of observing wildfire.

We include data to control for wildfire hazard potential (Dillon and Gibertson-Day 2020). The USFS releases geospatial data on the potential for a difficult wildfire suppression campaign. The wildfire hazard potential (WHP) layer is produced by the Forest Service’s Fire Modeling Institute

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[18] A community is formally identified as “disadvantaged” if it is measured as above the 90th percentile in one of several categories of environmental indicator. Additionally, they must be above the 65th percentile in low-income status. The eight environmental categories include (i) clean energy and energy efficiency, (ii) climate change, (iii) clean transit, (iv) affordable and sustainable housing, (v) reduction and remediation of legacy pollution, (vi) critical clean water and wastewater infrastructure, (vii) health burden, and (viii) training and workforce development.

and incorporates spatial layers of wildfire likelihood and intensity, vegetative fuel loads, and previous fire occurrence locations. The resultant raster layer is depicted at a 270-meter resolution and categorizes wildfire hazard in five tiers of hazard potential[19]. Hazard potential is important to our analysis as the probability of ignition does not fully capture the ambient risk a community is faced with; the intensity of that ignition plays an important role[20].

The type and concentration of vegetative fuels will confound the decision to use aviation in a given location. Information on wildfire fuels from the Anderson 13 Fire Behavior Fuel Models (Forest Service and Land Management 2020) is also included in the data. This raster layer measures vegetative fuel loads at a 30m resolution. Fuel load values are determined via satellite imagery based on fuel size, fuel type, surface area-to-volume ratios, and fuel attributes[21]. Including these data allows us to condition on a confounder in wildfire resource allocations at the community level; it's possible that suppression decisions could be made based on the type of fuels that surround homes, even after considering ignition probability and severity potential.

The relative terrain of a census tract is another critical determinant of decisions to use aviation to protect a particular community. We include data on elevation, terrain, aspect, and slope obtained from Open Topography and USGS Elevation Point Query (Gesch et al. 2009). These values account for the landscape of a census tract, which will drive suppression decisions for concerns of rapid fire spread (Storey et al. 2021). We also include controls for topography and slope because we believe that they are a valuable proxy for wind in our cross-sectional analysis. Wind conditions are an important factor in suppression decisions (Castellnou et al. 2019) due to its ability to drive the spread of wildfire. However, winds are subject to change over the course of a fire (Mahrt 2011) or even in a single day, making it implausible to control for this factor in our analysis. Scientific evidence exists that factors like topography and vegetation influence wind patterns (Wakes et al.

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[19] There are values in the WHP raster layer that are greater than seven, but characterize non-burnable land. We reclassify the WHP for those lands as 0 for our analysis.

[20] It is worth noting that the WHP raster layer does **not** forecast wildfires in the upcoming fire season(s). Rather, it depicts places where wildfires could be particularly intense conditional on ignition based on vegetative fuel loads and other factors.

[21] Example of a fuel attribute: living or dead?

2010). Therefore, we believe controlling for topography and fuels will account for any systemically disproportionate exposure a tract would have to wildfire due to the wind.

The last raster layer we incorporate in our analysis is the population density spatial data available from LANDSCAN (Bhadari et al. 2002). This layer uses information on existing housing/residential infrastructure and economic activity to model the population of an area at a 90m resolution. It's important to account for the relative concentration of individuals in a community as evidence suggests incident managers take that into account when allocating a resource to a particular location and it is highly correlated with the area burned (Haas, Calkin, and Thompson 2015). If we assume one of the primary objectives of incident management is to reduce damages to people/property, then protecting communities with higher population densities will be critical. Additionally, communities with a higher concentration of individuals living in them could be correlated with other features (like road access) that influence suppression strategies.

The final source of data we turn to for our analysis is the Protected Area Database for the United States (PAD-US), which contains geospatial information on resource lands, including which federal agency manages the land (Gergely and McKerrow 2016). These data are assembled from several different government agencies on resource lands into one vector layer. This information allows us to account for nuances in suppression strategy due to land management agency priorities.

We use census tracts as the geographic unit of analysis for several reasons. First, the Justice 40 initiative has developed definitions of disadvantaged communities at the census tract level[22]. Second, we believe that census tract borders are non-salient to incident managers; resources are unlikely to deliberately be allocated along these political boundaries[23]. Finally, there is high-quality socioeconomic data available at the census tract level from the U.S. Census Bureau[24]. Once we obtained the Justice 40 data, we trimmed our sample to only the census tracts inside the

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[22] It is worth noting that throughout this paper, we use the terms "census tract" and "community" interchangeably, as it is clear from recent legislation (White House 2022) that the federal government thinks of them in this way.

[23] Instead, patterns in resource allocation at the census tract level are going to be a function of other features of that community, such as biophysical or demographic factors

[24] The federal government updates these data frequently; our analysis leverages data accessed in June 2022

western Geographic Area Coordination Centers (GACCs), due to the region's higher prevalence of wildfire (Trouet et al. 2010) and public land (Olmstead, Kousky, and Sedjo 2012).

To further display how we combined data on wildfires, aviation, and demographic features of a community for our analysis, Figure 2.2 provides a visual depiction of the individual fires. The panel on the top (labeled A) maps the final perimeter of the 2017 La Tuna and Creek fires in California to determine which communities were deemed as "fire-affected". The black lines demarcate census tract boundaries, our geographic unit of analysis. The census tracts are shaded based on the share of residents that are ethnic minorities. The panel on the bottom (labeled B) repeats this for the 2020 Cameron Peak fire in Colorado. The darker pink interior perimeter represents the final fire perimeter that we use to determine which census tracts to include in our main sample. The blue lines on the map highlight where aviation was used in the suppression of wildfire damages, our measure of wildfire suppression effort.

If a census tract has any large wildfire burn in its area, we consider that tract to be "fire-affected" and include it in our sample. We determined that, out of the 18,003 census tracts in the western US, 1,120 of them had an MTBS wildfire burn within its borders and were thus included in our sample. The distribution of these fire-affected tracts is not uniform. Some wildfires impact large numbers of census tracts, evidenced by the La Tuna fire on top in Figure 2.2. Others may span fewer but more expansive tracts, like the Cameron Peak fire (bottom). This distinction highlights the heterogeneous nature of wildfire exposure across different landscapes.

The number of retardant drops allocated to each tract over our sample period is tabulated and included in our data as a measure of suppression effort. We also include a measure of LAT suppression expenditures within each tract as an alternative measure of effort. We do so by obtaining data from the Forest Service on one year's worth of LAT suppression expenditures. Then, we train a random forest model[25] to estimate the cost of each drop in our sample as a function of aircraft

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[25] See Section A1 in the Appendix for details about how this model was trained and implemented.

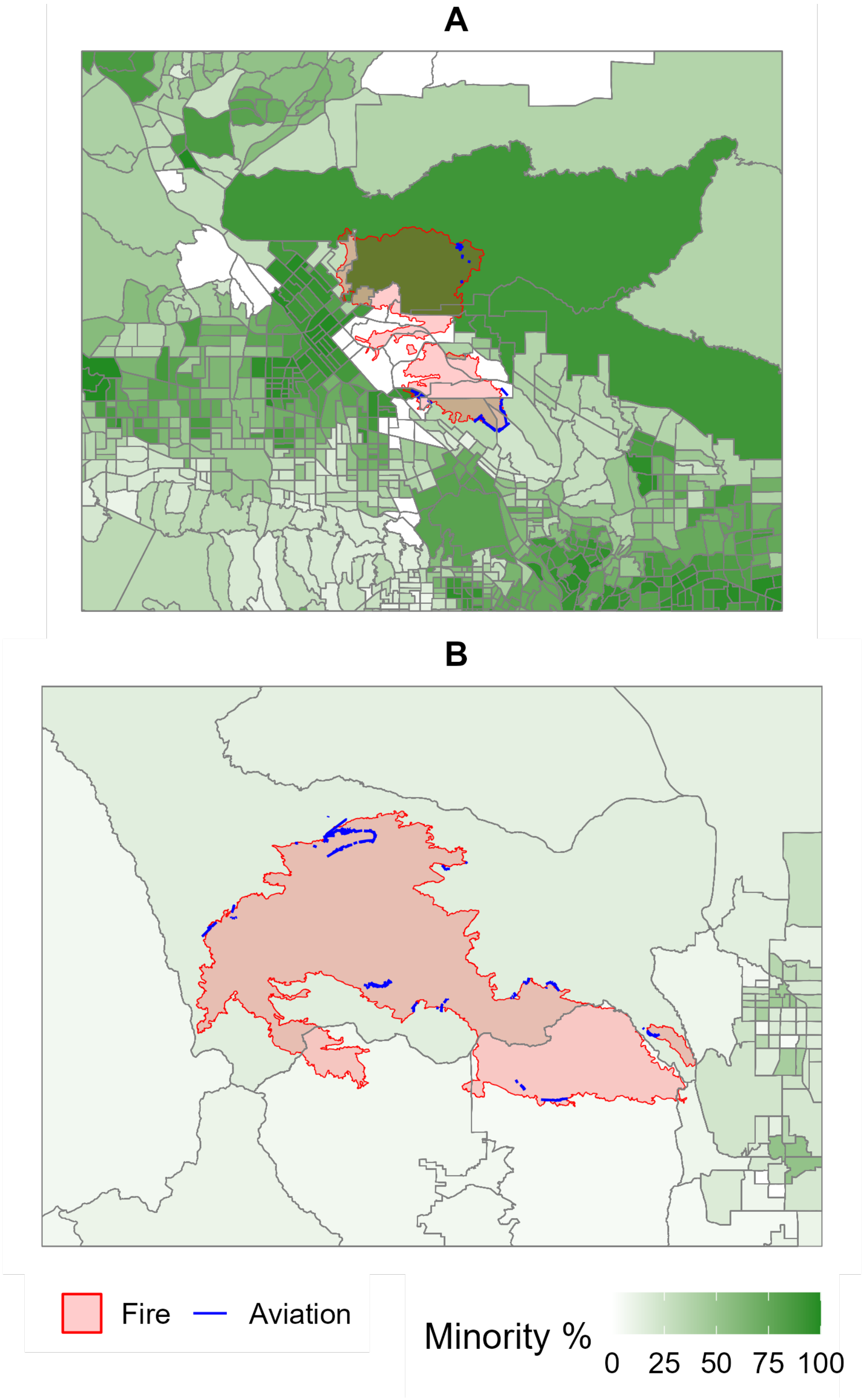

Figure 2.2: Map of aviation use and the share of minority residents in the communities threatened by the 2017 La Tuna fire (CA) and the 2020 Cameron Peak fire (CO)

type and gallons of retardant released. We aggregate the cost of all drops in each census tract in our data into one measure of suppression "investment".

We extract an area-weighted mean value for each factor at the census tract level using the previously mentioned raster layers on burn probability, wildfire hazard potential, population density, fuel concentrations/type, and terrain/elevation[26]. For time-varying layers, such as population density, we extract the value specific to the year of the fire. These values are then merged into our data frame using the unique census tract ID. We process all data using spatial data packages (raster, sf, terra, exactextractr) in the R program (**SF**; R Core Team 2022; A. Hijmans 2021; Dowle et al. 2021; R. J. Hijmans 2021). We also overlay PAD-US's vector layer of federal land management with our map of census tracts, then calculate the share of land in each tract managed by each federal land management agency.

2.2.3 Empirical Strategy

Aviation use in wildfire suppression may be influenced by socioeconomic factors across different census tracts. However, any apparent relationship between these factors and aviation use could be confounded by the correlation between socioeconomic characteristics and environmental factors such as topography and vegetation. Incident commanders prioritize protecting valuable assets like private property, with decisions often guided by fire behavior, which is closely tied to the surrounding environmental conditions. Firefighters are keenly aware of how topography and environmental conditions can influence fire behavior and often guide suppression effort to avoid more intense fire activity.

Our empirical challenge is to account for topographic and environmental characteristics in census tracts that would be expected to attract aviation effort. For example, Stonesifer, Calkin, Thompson, and Belval 2021 find that retardant drops from LATs are correlated with the terrain

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[26] We use the "exact_extract" package in R to acquire values from each layer

and fuel type of the targeted land[27]. We develop a regression model to estimate the correlation between aviation use and socioeconomic characteristics, conditional on topographic and environmental conditions that we expect incident commanders to be responsive toward.

We first examine the correlation among key variables in our analysis to better understand the interplay between wildfire risk and socioeconomic characteristics of a community. Figure 2.3 depicts the correlation between key variables in our analysis. The final column shows correlation values indicating that the likelihood of receiving aviation is positively correlated with WHP, burn probability, elevation, and several other biophysical characteristics of a census tract, while negatively correlated with population density. These biophysical factors are, therefore, confounders in the decision to allocate aviation effort to a particular census tract.

We test our hypotheses that aviation effort systematically differs across socioeconomic characteristics by developing a hurdle regression model. Aviation effort may differ on the extensive (whether used or not) and the intensive margin (if used, how much). Hurdle models are well-suited for modeling situations with a mass point at a certain value in a distribution, especially zero (Neelon, Ghosh, and Loebs 2013; Yen 1993). Hurdle models are frequently used in demand analysis (Yen and Huang 1996; Lin and Milon 1993; Ricker-Gilbert, Jayne, and Chirwa 2011) since there is a high volume of zeros in the dependent variable, but it has been used to model other situations as well (Yen 1993; Neelon, Ghosh, and Loebs 2013).

We specify our Hurdle model in two separate parts, first as the binary decision to utilize aviation in a census tract:

$$S_c = \begin{cases} 1 \quad \text{if} \quad Z_c\gamma + F_c\alpha + \epsilon_c > 0 \\ 0 \quad \text{if} \quad \text{otherwise} \end{cases} \tag{2.6}$$

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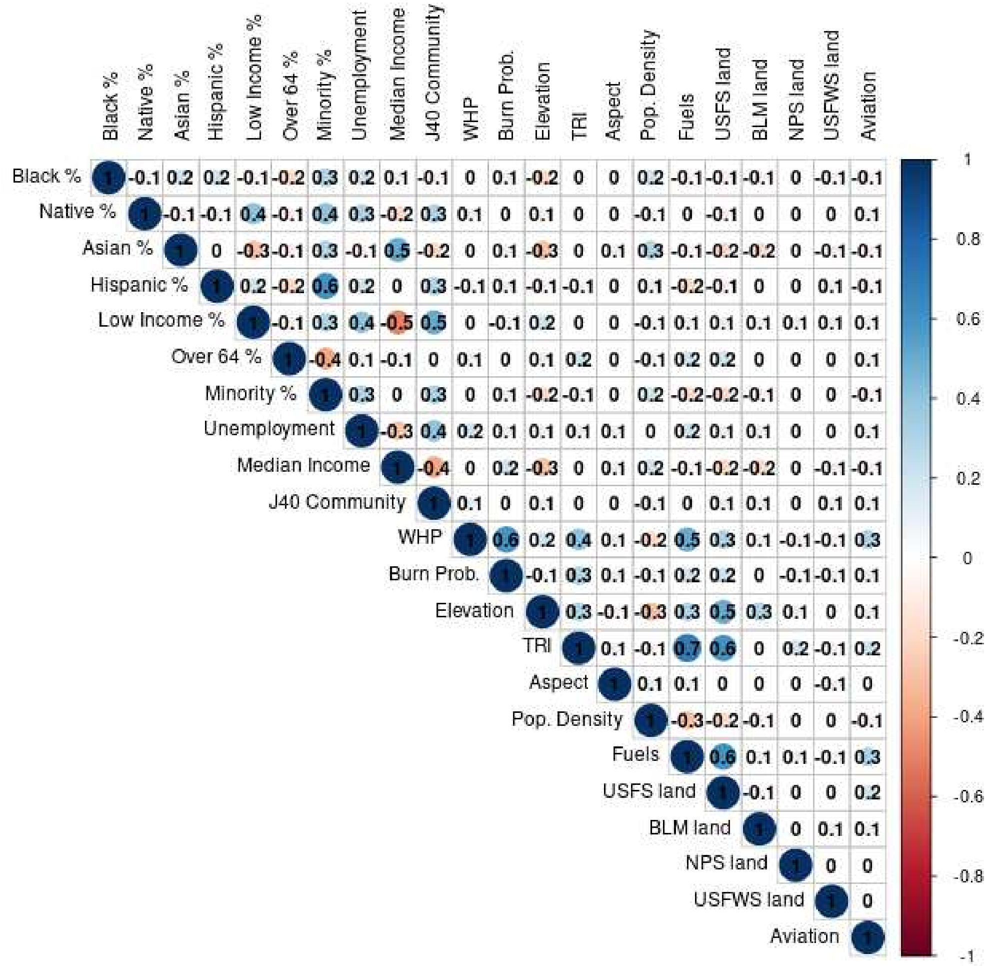
[27] It is worth noting that the fuel types that the authors find are correlated with aviation use are **not** the preferred fuel types for using aviation according to USFS effectiveness guidelines (Stonesifer, Calkin, Thompson, and Stockmann 2016)



	Black %	Native %	Asian %	Hispanic %	Low Income %	Over 64 %	Minority %	Unemployment	Median Income	J40 Community	WHP	Burn Prob.	Elevation	TRI	Aspect	Pop. Density	Fuels	USFS land	BLM land	NPS land	USFWS land	Aviation
Black %	1	-0.1	0.2	0.2	-0.1	-0.2	0.3	0.2	0.1	-0.1	0	0.1	-0.2	0	0	0.2	-0.1	-0.1	-0.1	0	-0.1	-0.1
Native %		1	-0.1	-0.1	0.4	-0.1	0.4	0.3	-0.2	0.3	0.1	0	0.1	0	0	-0.1	0	-0.1	0	0	0	0.1
Asian %			1	0	-0.3	-0.1	0.3	-0.1	0.5	-0.2	0	0.1	-0.3	0	0.1	0.3	-0.1	-0.2	-0.2	0	-0.1	-0.1
Hispanic %				1	0.2	-0.2	0.6	0.2	0	0.3	-0.1	0.1	-0.1	-0.1	0	0.1	-0.2	-0.1	0	0	0.1	-0.1
Low Income %					1	-0.1	0.3	0.4	-0.5	0.5	0	-0.1	0.2	0	0	-0.1	0.1	0.1	0.1	0.1	0.1	0.1
Over 64 %						1	-0.4	0.1	-0.1	0	0.1	0	0.1	0.2	0	-0.1	0.2	0.2	0	0	0	0.1
Minority %							1	0.3	0	0.3	0	0.1	-0.2	-0.1	0	0.2	-0.2	-0.2	-0.1	0	0	-0.1
Unemployment								1	-0.3	0.4	0.2	0.1	0.1	0.1	0.1	0	0.2	0.1	0.1	0	0	0.1
Median Income									1	-0.4	0	0.2	-0.3	0	0.1	0.2	-0.1	-0.2	-0.2	0	-0.1	-0.1
J40 Community										1	0.1	0	0.1	0	0	-0.1	0	0.1	0.1	0	0.1	0.1
WHP											1	0.6	0.2	0.4	0.1	-0.2	0.5	0.3	0.1	-0.1	-0.1	0.3
Burn Prob.												1	-0.1	0.3	0.1	-0.1	0.2	0.2	0	-0.1	-0.1	0.1
Elevation													1	0.3	-0.1	-0.3	0.3	0.5	0.3	0.1	0	0.1
TRI														1	0.1	-0.1	0.7	0.6	0	0.2	-0.1	0.2
Aspect															1	0.1	0.1	0	0	0	-0.1	0
Pop. Density																1	-0.3	-0.2	-0.1	0	0	-0.1
Fuels																	1	0.6	0.1	0.1	-0.1	0.3
USFS land																		1	-0.1	0	0	0.2
BLM land																			1	0	0.1	0.1
NPS land																				1	0	0
USFWS land																					1	0
Aviation																						1

Figure 2.3: Correlation Matrix of covariates in our main sample

Our initial outcome variable, E_c, is a binary indicator of whether or not census tract c received aviation at any time during our sample. Z_c is a vector of socioeconomic controls. F_c is a vector of biophysical controls: wildfire hazard potential, population density, burn probability, vegetative fuel loads, elevation, terrain ruggedness, and the share of land managed by a federal agency. It is vital to account for these features since higher income and race can be associated with residing in areas with more environmental amenities. It would be a mistake to assume a resource was deployed to a specific location due to the income of the adjacent community when the deployment was actually made due to heavy fuel concentrations.

Each control in our sample is transformed to better model the decision-making process of resource allocation. Wildfire resource decisions are often made in terms of relative risk (NIFC 2019), rather than in absolute terms. Each biophysical control is re-calculated in terms of its percentile rank. Then we split them into five separate bins based on their order in that ranking. We estimate a model with a GACC fixed effect as well, to account for any time-invariant heterogeneity in suppression strategy at the level where resource allocations are initially made.

We then model the choice for *how much* aviation to use in a census tract using an exponential model as follows:

$$h_c^* = exp(X_c\beta + G_c\theta + \mu_c) \tag{2.7}$$

h_c^* represents the intensive margin measure of LAT suppression effort; the number of retardant drops in a census tract during our sample period. Identical to our extensive margin estimation, X_c is a vector of socioeconomic controls, and G_c is a vector of biophysical factors.

Taking both of these functions together, we can represent our Hurdle model with the following log-likelihood function, where we first condition on biophysical factors in aviation decisions:

$$\mathcal{LL}(\theta,\gamma,\alpha,\beta|E,S) = \prod_{S_c=0} ln[\Phi(-{z_c}'\gamma - {f_c}'\alpha)] + \prod_{S_c=1} ln[1-\Phi(-{z_c}'\gamma - {f_c}'\alpha)] + \prod_{S_c=1} ln[\frac{1}{\sigma}(ln(y_c) - {x_c}'\beta - {g_c}'\theta)) - ln(\sigma) - ln(y_c))] \tag{2.8}$$

After estimating a baseline model with Equation (7), we estimate two separate models to see if there is any census tract heterogeneity based on the socioeconomic characteristics of a census tract. First, we estimate a model that replaces the measure of resident share of "minorities" (not broken out by race), with a percentage of residents that are Black, Hispanic, Asian, or another ethnic minority group. Second, we replace our binary indicator for a census tract being "environmentally disadvantaged" according to the federal government with a series of indicators if a tract exceeds one of the eight thresholds that qualify it for the Justice 40 designation.

It is worth noting that we are not making any causal claims with the results we derive from our econometric model, nor do we claim to formally identify the effect socioeconomic characteristics of a community could have on wildfire suppression strategy. Instead, we believe our results will indicate whether there is a relationship between wildfire suppression response and the socioeconomic features of the communities in proximity. Coefficient estimates, even if they are significant, should not be interpreted as responses to the socioeconomic characteristics of a community.

2.3 Results

2.3.1 Summary Statistics

We begin our analysis by using the data on retardant drops to test the assumption that census tracts affected by different wildfires are valid counterfactuals. Figure 2.4 shows the distribution of the number of unique fires visited by LATs in a single day. Most LATs tend to fight fire on a single incident on the days they are active, but Figure 2.4 clearly shows that it is not uncommon for LATs to engage suppression on multiple fires in one day. Therefore, we contend that census tracts on different wildfires are valid counterfactuals to each other due to resource mobility. The mobility of LATs, as illustrated by their daily assignments to multiple incidents, supports the use of census tracts on different wildfires as our unit of analysis.

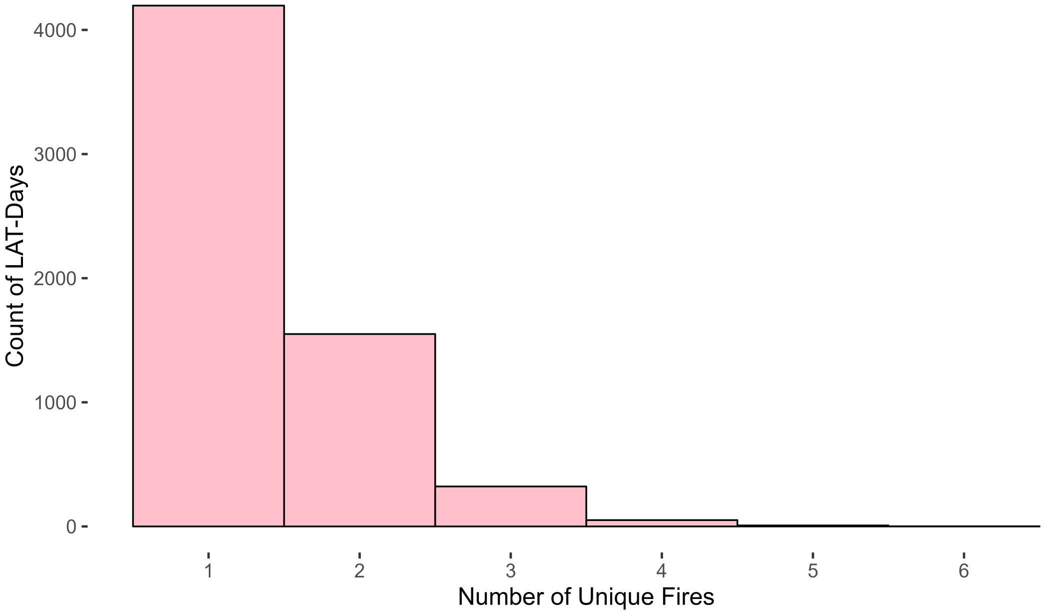


Figure 2.4: Histogram of unique fires visited by a LAT within day

In our sample of fire-affected census tracts, 713 tracts received effort through wildfire aviation resources, while 407 did not. Figure 2.5 compares the means of several key variables in our analysis broken out by whether they received aviation effort. Table A1 in the Appendix shows these estimates in table form, along with summary statistics of covariates in our econometric model. Our unconditional analysis of the locations where LAT effort was assigned does not reveal any significant evidence of inequality across socioeconomic lines. Figure 2.5 shows that the fire-affected census tracts that *don't* receive aviation tend to have a higher population share of ethnic minorities, albeit only a slight difference (28% vs. 26% according to Table A1).

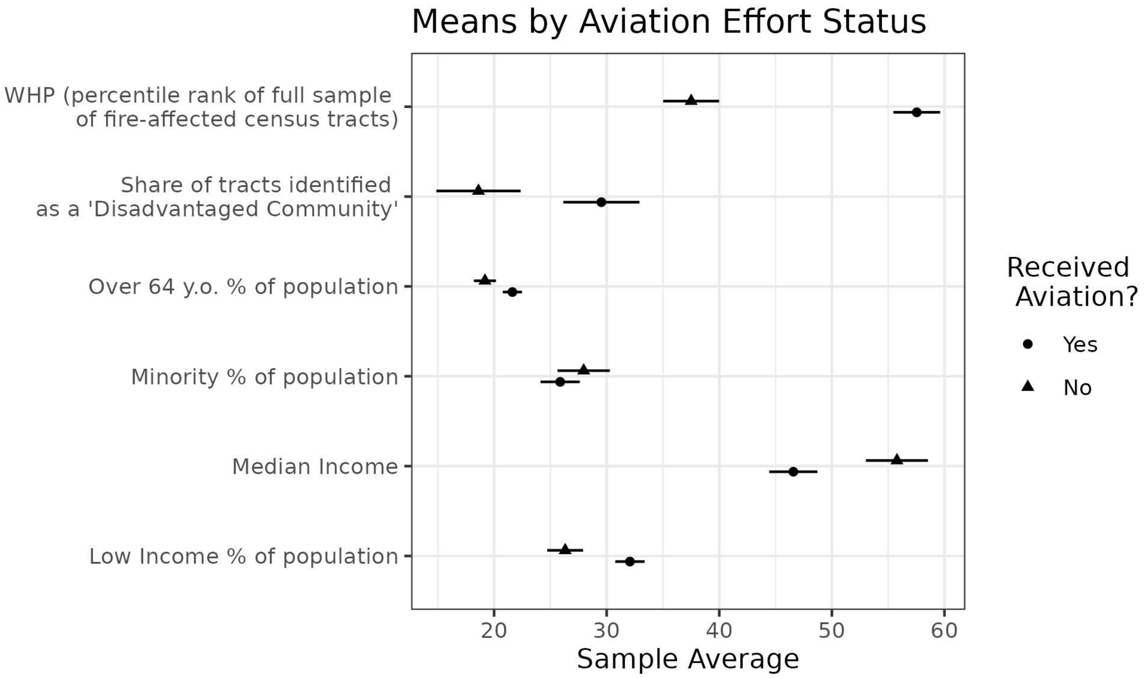


Figure 2.5: Distribution of several key variables in our analysis

Figure 2.5 also shows that communities that receive aviation suppression effort have a higher share of "low-income" residents (32% of the population in tracts which receive aviation effort vs. 27% in the tracts which don't) and a lower median income in the treated census tracts ($67,623 vs. $75,190 according to Table A1). However, our confidence intervals in Figure 2.5 suggest that the difference in low-income resident percentage is not statistically different. Similarly, we find that census tracts that receive retardant drops are more likely to be an "environmentally disadvantaged" community (29.2% of communities that receive aviation are Justice 40 communities, compared to 18.9% of the ones that don't.). Our fire-affected census tracts that receive aviation also tend to have a lower population share of individuals over the age of 64 (22% vs. 19%). These patterns are insightful regarding the equality of LAT assignments, true explorations of equity consider the suppression needs of the communities threatened.

Aviation is used more in communities that face significant threat of disastrous wildfire events, evidenced by its use in communities with greater wildfire hazard potential (WHP) and burn probability. The tracts that receive LAT retardant drops appear to be 17 percentile points higher in WHP and 15 percentile points greater in burn probability, compared to those that don't receive them. Intuitively, the communities that receive aviation also have a lower population density (41st percentile) than the tracts that don't (54th percentile); indicative of more rural communities in the WUI.

2.3.2 Main specification

We investigate the correlation between aviation use and socioeconomic characteristics, conditional on environmental factors that influence wildfire behavior. Aviation "use" is modeled in two ways: first as the total number of retardant drops released into a community, then as the total dollars spent on LAT suppression. Regressions are estimated using the "churdle" command in Stata 15. Table 2.1 presents the results of the Hurdle model that we use to study the intensive and extensive margin decisions.

Column 1 contains coefficient estimates for a model simply estimating the correlation between socioeconomic measures and the number of retardant drops in a community with no biophysical controls. Column 2 contains similar coefficient estimates, now including controls at the tract level for biophysical factors, like WHP (Wildfire Hazard Potential), burn probability, and population density. Column 3 represents our preferred specification, including all of the same controls as before, but now includes a GACC fixed effect. All standard errors are clustered at the "pyrome"[28] level. Columns 4 through 6 contain a comparable trilogy of specifications that use a different dependent variable: LAT suppression expenditures.

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[28] Pyromes are a geographic measure of area based on common wildfire characteristics (Archibald et al. 2013)

Table 2.1 presents the coefficient estimates of the Hurdle model in two parts. The bottom panel models how socioeconomic factors correlate with the binary decision of whether or not to use aviation to suppress wildfire in a particular census tract (extensive margin). The top panel models the correlation of socioeconomic factors with the *amount* of wildfire suppression allocated to a census tract (intensive margin), measured as total drops in Columns 1 through 3 and total expenditures in Columns 4 through 6.

We find some evidence of inequity when ignoring biophysical controls. We find a positive correlation between the share of residents that qualify as "low-income" and the likelihood of a tract receiving retardant drops or LAT suppression expenditures. This suggests that a 10% increase in the share of census tract residents that are below the poverty threshold would be correlated with an increase of 11.8% in the likelihood of receiving a retardant drops or 12.9% increased likelihood of being the recipient of suppression investment via airtanker. The correlation between low-income residents and LAT suppression expenditures remains positive and statistically significant when we include controls in Column 5 and a fixed effect in Column 6[29].

We find that the unemployment rate and median income of a census tract are correlated with the likelihood of receiving LAT suppression, but both are sensitive to the set of controls used in the model. Unemployment rate is only statistically significant when we don't condition on biophysical characteristics. Median income is only signficant when we do control for those factors. In our preferred model, a 10% increase in the median income of a census tract would correlate with a 4.29% higher likelihood of receiving LAT suppression. This could be evidence of inequity, but it does not appear that lower income communities have a lower likelihood of receiving this resource, evidenced by the result in the second row(s) in the bottom panel[30].

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[29] The extensive margin results are different for LAT suppression and LAT costs because the ATUs malfunction for some drops, not recording the amount of retardant released. Our calculation for the cost of each drop is largely a function of the amount of retardant released (see Section A1). The drops where the ATU malfunctions will appear to be costless according to our calculation. Table A8 is included in the Appendix using only a subset of drops where the amount of retardant released was recorded.

[30] We also don't find lower income communities to receive LAT suppression in smaller magnitudes either (evidenced by top panel), meaning the increased likelihood of LAT effort for higher income communities isn't coming at the expense of smaller allocations of LAT effort for lower income ones.

Table 2.1: Hurdle model estimation of the correlation of LAT wildfire suppression with socioeconomic characteristics of a community (census tract level)

	(1) LAT Drops	(2) LAT Drops	(3) LAT drops	(4) LAT costs	(5) LAT costs	(6) LAT costs
Intensive						
Minority %	-0.484*	0.102	0.086	-0.294	0.336	0.340
	(0.264)	(0.293)	(0.292)	(0.277)	(0.273)	(0.280)
Low-Income %	0.276	-0.230	-0.259	0.001	-0.444	-0.484
	(0.439)	(0.420)	(0.416)	(0.438)	(0.372)	(0.369)
Over 64 y.o. %	0.792	0.118	0.217	1.366**	0.424	0.547
	(0.558)	(0.386)	(0.411)	(0.657)	(0.462)	(0.522)
Unemployment Rate	0.563	-0.635	-0.773	0.813	-0.342	-0.460
	(0.596)	(0.572)	(0.616)	(0.607)	(0.544)	(0.578)
Median Income ($1000s)	-5.652**	0.686	-0.562	-6.158***	0.628	-0.557
	(2.255)	(2.708)	(2.714)	(2.265)	(2.639)	(2.591)
'Disadvantaged' Community	0.130	0.213*	0.202*	0.089	0.176	0.164
	(0.137)	(0.121)	(0.115)	(0.136)	(0.124)	(0.117)
Extensive						
Minority %	-0.641**	0.218	0.209	-0.687**	0.129	0.042
	(0.296)	(0.250)	(0.233)	(0.300)	(0.304)	(0.276)
Low-Income %	1.122***	0.579	0.520	1.209***	0.706*	0.676*
	(0.289)	(0.366)	(0.367)	(0.327)	(0.410)	(0.397)
Over 64 y.o. %	0.707	-0.293	-0.056	0.501	-0.706*	-0.592
	(0.628)	(0.545)	(0.588)	(0.572)	(0.428)	(0.439)
Unemployment Rate	2.162***	0.812	0.834	2.011***	0.610	0.544
	(0.761)	(0.618)	(0.600)	(0.738)	(0.601)	(0.581)
Median Income ($1000s)	1.241	5.424***	4.290**	1.627	5.664***	4.534**
	(1.777)	(2.003)	(2.104)	(1.902)	(2.035)	(1.940)
'Disadvantaged' Community	0.108	-0.017	0.021	0.146	0.065	0.104
	(0.132)	(0.129)	(0.136)	(0.136)	(0.133)	(0.140)
Land management controls (binned)	No	Yes	Yes	No	Yes	Yes
Biophysical controls (binned)	No	Yes	Yes	No	Yes	Yes
Population density controls (binned)	No	Yes	Yes	No	Yes	Yes
GACC fixed effects	No	No	Yes	No	No	Yes
Observations	1,102	1,102	1,102	1,102	1,102	1,102

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We don't find a statistically significant correlation between any of our socioeconomic variables and our intensive margin measure of suppression effort when we use our full set of controls. The designation of a community as "environmentally disadvantaged" by the federal government is displayed in the sixth row of the top panel. We don't observe a correlation between a community being disadvantaged and the likelihood of LAT resource deployments in Column 1. We observe a statistically significant and positive correlation between the Justice 40 designation and the amount of LAT drops the community receives once we condition on factors relevant to wildfire suppression. That correlation remains when we include a regional fixed effect in our model, attenuating only slightly in magnitude. This coefficient suggests that a fire-affected tract designated as "environmentally disadvantaged" is correlated with receiving 22% more drops, conditional on receiving any. We observe a similar progression of the Justice 40 coefficient's magnitude across the models that use LAT expenditures in a census tract as the dependent variable. However, we are never able to conclude that the correlation is statistically different from zero in any of our models.

We find little evidence of median income being correlated with LAT allocations on the intensive margin, despite communities with a higher median income having a higher likelihood of receiving effort from them. Median income is negatively correlated with the magnitude of LAT suppression (-5.652). This coefficient suggests that if a census tract observed a 10% increase in median income, they would be 5.61% less likely to receive aerial suppression support. We find the same result in the model with LAT expenses as the dependent variable (Column 4). Once we condition on biophysical factors in Column 2 & 5, we find that the median income of a census tract is not correlated with the extensive margin measure of suppression effort. This remains true in our models that include GACC fixed effects in Columns 3 & 6. Meanwhile, unemployment never appears to be significantly correlated with a tract's likelihood of receiving aviation in any of our specifications.

Table A2 in the Appendix reports the marginal effects of our primary Hurdle model. The marginal effect estimates have an intuitive interpretation in the context of wildfire suppression; a one percentage point increase in our demographic resident share variables corresponds to a change in the overall[31] aviation effort allocated to a census tract. As an example, Column 1 of Table A2 (no controls or fixed effects) suggests that a 10% increase in the share of minority residents in a fire-affected community would correspond to 2.3 fewer retardant drops.

2.3.3 Robustness

Coefficient Decomposition

We evaluated the sensitivity of our results to the different control sets employed by plotting the coefficient estimates and standard errors for our key demographic variables with each possible combination of explanatory variables in our Hurdle model. These plots give us an idea of how precise the null finding is on the relationship between demographic features of a census tract and LAT suppression effort. Figures A1 and A2 (see Appendix) help make sense of our previous findings by decomposing the coefficient estimate on a tract's share of minority residents based on the other controls included in the model. This is repeated for the coefficient estimate on low-income resident share in Figures A3 and A4 (in the Appendix) and the Justice 40 designation in Figures A5 and A6.

We find the coefficient estimate on a tract's share of minority residents to be robust to the inclusion of most biophysical controls. Prior to controlling for any other factors, we find the minority share to be negatively correlated with allocations of LAT suppression effort. There doesn't seem to be one control that absorbs that effect, though. We do find that the coefficient estimate on the share of low-income residents is sensitive to population density, both on the extensive and intensive margins. Our plots for the Justice 40 coefficient show that no matter which combination of controls we use in our Hurdle model, being designated as a target for federal funds is positively correlated with the likelihood of receiving aerial suppression.

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[31] This is opposed to our previous table that models how a change in one of our demographic variables corresponds to either (i) a change in the probability of receiving aviation or (ii) a response in the amount of aviation applied to a census tract.

Block Group-level analysis

We further evaluated the robustness of our socioeconomic variable coefficient estimates by varying our spatial definition of a "community". Table A4 (see Appendix) contains results estimated using the econometric model specified in Equations 7 - 9, where the geographic unit c is a census block group rather than a census tract. Census block groups are smaller than census tracts in spatial extent. Using the block group as our unit provides an opportunity to evaluate the robustness of our findings[32]. We are unable to estimate the correlation between the federal designation of "disadvantaged" and LAT suppression in a block group-level analysis, as the Justice 40 thresholds are only met at the tract level.

Estimating our model using a smaller spatial scale of analysis doesn't change any takeaways regarding an inequitable relationship between the racial makeup of a fire-affected community and the LAT suppression effort they are allocated. We find a positive coefficient on the share of minority residents and suppression effort. This is true on both the extensive and intensive margins. This suggests that, while there is statistical significance on the coefficient, these communities aren't systematically under-allocated resources as a function of their race.

We do find that the relationship between income and LAT allocations is sensitive to the spatial scale of analysis. Similar to the tract-level analysis, there is a positive correlation between median income and LAT suppression on the extensive margin. Unlike the tract-level analysis, it does appear that this increased likelihood is coming at the expense of fewer LAT resources allocated to low-income communities. According to the coefficient estimate, a 10% increase in the share of low-income residents would correspond to allocations of LAT suppression effort that are 13.2% smaller in magnitude (or 9.82% fewer dollars invested in LAT suppression). We do not find a statistically significant effect on the marginal effect of the low-income resident share at the block group level, evidenced by Table A5.

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[32] Especially since there is evidence in the environmental justice literature that studies conducted at smaller geographic scales can capture environmental damages with more accuracy (Carvalho, Del Campo, and De Carvalho Cabral 2022)

2.3.4 Fire-level analysis

We extend our analysis of the equity in wildfire suppression up to the fire-level to see if socioeconomic factors are correlated with the resource management of the regional office. Our primary Hurdle model is used to produce estimates with the supplementary fire-level sample described in Section A2 (see Appendix). Table 2.2 (see Appendix) contains coefficient estimates for this incident-level model. It is structured identically to Table 2.1; the bottom panel displays coefficients for the extensive margin relationships with the dependent variable; the top panel shows the intensive margin estimates. Columns 1 through 3 contain results with incident-wide suppression effort as the dependent variable (measured by retardant drops), Columns 4 through 6 show the same for LAT expenses.

Table 2.2 doesn't reveal strong evidence of an inequitable allocation of LAT effort. There are no socioeconomic variables on the extensive margin that have a negative and significant coefficient in our full model (Column 3, bottom panel)[33]. This means we have no evidence that socioeconomic factors are correlated with a lower likelihood of a LAT being allocated to a wildfire. We do find that fires that threaten more wealthy and elderly populations receive more LAT drops, consistent with the findings of Wibbenmeyer and Robertson 2022.

This finding holds for the likelihood of receiving federal investment in suppression through LAT. We only find statistical evidence of a negative relationship between the magnitude of LAT suppression and one socioeconomic variable: unemployment rate. The top panel of Column 3 suggests that a 10% increase in the unemployment rate of the communities threatened by a wildfire would correlate with a -1.8% decline in the amount of LAT drops on that fire. We tested if there is heterogeneity in the correlation between firefighting effort by race, similar to our community-level analysis. Figure 2.6 shows that there is not one minority group that has a negative statistical correlation with the extensive or intensive margin decisions on aerial suppression effort.

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[33] In these models, median income has a positive coefficient on both margins. However, those estimates are small in magnitude. A 10% increase in the median income of a community would correlate with a 0.03% increase in the probability of receiving a LAT and an allocation of retardant drops that is larger by less than 0.01%

Table 2.2: Hurdle model estimation of the correlation of LAT wildfire suppression with socioeconomic characteristics of surrounding communities (fire level)

	(1) LAT Drops	(2) LAT Drops	(3) LAT drops	(4) Total LATs	(5) Total LATs	(6) Total LATs
Intensive						
Minority %	0.568**	0.593**	0.364	0.166	0.239*	0.276**
	(0.253)	(0.244)	(0.238)	(0.159)	(0.130)	(0.116)
Low-Income %	0.367	0.150	-0.112	-0.049	-0.225	-0.328
	(0.401)	(0.391)	(0.373)	(0.231)	(0.242)	(0.223)
Over 64 y.o. %	2.551***	2.155***	2.149***	1.361***	1.039***	1.161***
	(0.707)	(0.609)	(0.629)	(0.414)	(0.294)	(0.289)
Unemployment Rate	-0.773	-1.019	-1.810***	-0.421	-0.557	-0.868**
	(0.887)	(0.725)	(0.664)	(0.464)	(0.364)	(0.363)
Median Income ($1000s)	0.012***	0.011***	0.005*	0.005***	0.005***	0.003**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
Extensive						
Minority %	0.794	0.548	0.513	0.794	0.548	0.513
	(0.897)	(0.933)	(1.010)	(0.897)	(0.933)	(1.010)
Low-Income %	0.859	1.250	1.332	0.859	1.250	1.332
	(1.471)	(1.113)	(1.194)	(1.471)	(1.113)	(1.194)
Over 64 y.o. %	-1.492	-0.822	-1.150	-1.492	-0.822	-1.150
	(1.739)	(1.544)	(1.718)	(1.739)	(1.544)	(1.718)
Unemployment Rate	-0.412	0.542	0.770	-0.412	0.542	0.770
	(1.197)	(1.506)	(1.706)	(1.197)	(1.506)	(1.706)
Median Income ($1000s)	0.023*	0.028**	0.031*	0.023*	0.028**	0.031*
	(0.014)	(0.014)	(0.016)	(0.014)	(0.014)	(0.016)
Land management controls (binned)	No	Yes	Yes	No	Yes	Yes
Biophysical controls (binned)	No	Yes	Yes	No	Yes	Yes
Population density controls (binned)	No	Yes	Yes	No	Yes	Yes
GACC fixed effects	No	No	Yes	No	No	Yes
Observations	659	653	653	659	653	653

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

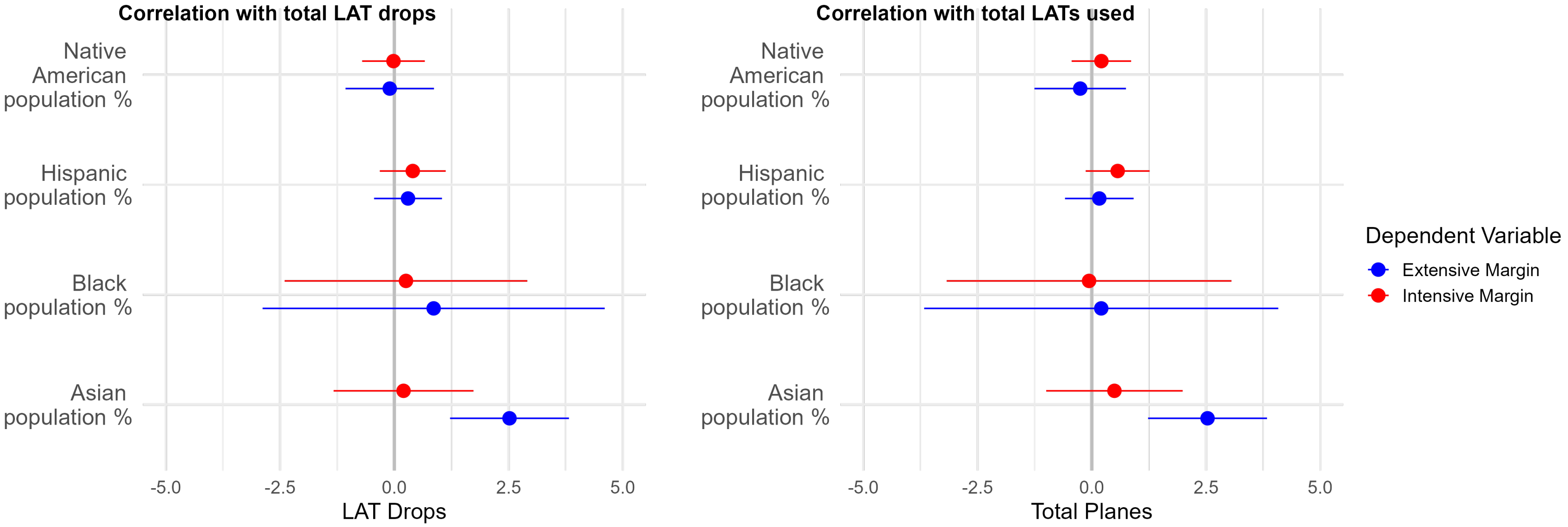

Figure 2.6: Heterogeneity in the correlation between minority % and LAT allocations based on racial group (fire-level)

We're not solely interested in the amount of aviation that was allocated to a wildfire as a function of socioeconomic factors; we're also curious if there's a correlation with the effort that *didn't* get allocated. We re-produce estimates using denied LAT requests as the dependent variable. This analysis can only be conducted with our sample of wildfires, as resources are requested from the regional office at the fire-level. Table 2.2 contains coefficient estimates for this model. We only report coefficient estimates for the extensive margin for this model[34].

The only socioeconomic variable measured at the fire-level that has any observable statistical relationship with denied requests (also termed UTFs) for aircraft is the share of residents over 64. According to Column 3 of Table 2.2, a 10% increase in the share of residents that are older than 64 living in a community would correlate with a decreased likelihood of being denied a LAT by about 1.4%. None of the other variables of interest had coefficient estimates that were statistically significant, true for every specification. Intuitively, we observe identical coefficients between our UTF and weighted UTF models for the extensive margin decision to deny a LAT.

2.4 Discussion

Our results suggest that socioeconomic characteristics of a community have minimal correlation with the likelihood of receiving suppression effort from a LAT after conditioning on biophysical factors. Of those characteristics, only the low-income resident share of a community is correlated with aerial suppression effort allocations that are smaller in magnitude (at the census block group level). The concentration of specific racial groups does not appear to be a significant factor in decisions to use aviation on either the intensive or extensive margin.[35] This was true both in our model which included a simple measure of a tract's minority population and our model estimating if there was any racial heterogeneity.

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[34] It is not clear how we should interpret intensive margin results from this model, or if it will be useful in analyzing the equity of resource allocations beyond extensive margin results.

[35] The one exception to this: a census tract's share of Asian residents is positively correlated with aviation allocations on the extensive margin.

Table 2.3: Hurdle model estimation of the correlation of rejected LAT requests (UTFs) with socioeconomic characteristics of surrounding communities (fire level)

	(1) LAT UTFs	(2) LAT UTFs	(3) LAT UTFs
Extensive			
Minority %	-0.345	-0.303	-0.242
	(0.296)	(0.291)	(0.309)
Low-Income %	-0.556	-0.688	-0.857*
	(0.487)	(0.478)	(0.491)
Over 64 y.o. %	-1.531*	-1.650**	-1.394*
	(0.789)	(0.782)	(0.759)
Median Income	-0.003	-0.001	-0.005
	(0.003)	(0.003)	(0.003)
Unemployment Rate	-0.199	-0.271	-0.563
	(0.666)	(0.619)	(0.672)
Land management controls (binned)	No	Yes	Yes
Biophysical controls (binned)	No	Yes	Yes
Population density controls (binned)	No	Yes	Yes
GACC fixed effects	No	No	Yes
Observations	659	653	653

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We find mixed results on our other demographic variables, such as measures of the population of a community's age or income, between our different specifications. It does seem that a community's elderly population tends to have a positive correlation after accounting for variation in race. Table A2 indicates that a one percentage point increase in a census tract's population over 64 years old corresponds to .205 more LAT drops. A 25% increase in the elderly population would be correlated with an additional drop, given the average census tract in our sample has 20.4% of residents over the age of 64. It's plausible that since elderly people often live in high concentrations at places like nursing homes or retirement communities, the population share of elderly people could be a direct determinant of resource assignments. The share of a census tract that is considered low-income is never correlated with LAT suppression effort in any of our models using the full set of controls, aside from an increased likelihood of receiving investment in suppression via LAT.

In general, we did not find significant evidence of inequity in the allocation of LAT retardant drops. Retardant drops are not uniform, though. LATs can vary on several margins, including the volume of retardant that they can hold. There are also quality differences in these aircraft that are often captured in their cost. It's theoretically possible that incident managers or regional coordinators could allocate the preferred aircraft (with increased firefighting capacity) to the communities with more rich and white residents. Our models that use LAT costs as the dependent variable don't lend evidence to inequity by cost.

Our results are consistent with findings documented in Wibbenmeyer and Robertson 2022, despite the different units of analysis and focus of the studies. They find that census tracts that reside in areas with the highest wildfire hazard potential and experience the most wildfire tend to be older and less ethnically diverse. We find in Table A1 that aviation is used in communities that are older and less ethnically diverse. Our means comparison (in Table A1) diverges from their findings in one specific way; they find that homes that face the most significant threat of wildfire tend to be wealthier, while we find that census tracts that receive aviation support have a higher proportion of “low-income" residents[36]. Figures A1 and A2 further support their finding that white households are more likely to live in areas at greater risk of wildfire. It appears that communities with a higher share of minorities are less likely to receive aerial suppression effort until we control for biophysical characteristics, including those that are seen as environmental amenities like fuel concentrations or access to public land.

There are two other interesting takeaways from our plots depicting coefficient estimates and standard errors for all possible control set combinations. First, the plots of the coefficient estimates for our low-income share variable[37] (Figure A3 and A4) highlight the importance of controlling for population density. Models that don't condition results on population density show that communities with more low-income residents are more likely to be allocated our measure of suppression resources[38]. Second, while we estimate a null correlation between the Justice 40 classification and

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[36] Our means comparison, with respect to correlations between low-income communities and wildfire outcomes, are consistent with another census tract level analysis; Masri, Scaduto, et al. 2021

[37] This trend is also observable in our minority share plots as well.

[38] We estimate a negative coefficient on this variable in our full specification; removing any single control for our model still results in a negative coefficient, save for population density.

either measure of aerial suppression effort, Figures A5 and A6 show that this estimate is robust across all different specifications.

Only two of the criteria that determine if a census tract can be designated as a "Justice 40 community" by the federal government were significantly correlated with the likelihood of receiving aviation effort (See Figures A8 or Table A7): pollution exposure and energy burden. The coefficient estimate on the "pollution exposure" category was negative on the extensive margin. These communities qualify for the designation if they are in close proximity to mines, Superfund sites, or other forms of legacy pollution. It's possible that these census tracts have fewer natural amenities due to the historical presence of polluting industry, resulting in reduced ambient wildfire risk.

The largest magnitude on any of our coefficients for the Justice 40 indicators belongs to tracts that are above the 90th percentile for "traffic exposure". This finding is consistent with wildfire suppression strategy leveraging roads as control points (Thompson, Gannon, and Caggiano 2021), as they have the ability to provide a fuel break, which complements effort provided by aviation, engine(s), or firefighter(s). All else equal, if two census tracts only differ in the mileage of road contained, the one with a higher concentration of pavement/gravel fuel breaks will naturally have a higher probability of receiving suppression inputs. The presence of more roads is likely to be correlated with more homes (Hawbaker et al. 2005), another determinant of suppression effort (Bayham and Yoder 2020).

The negative correlation between the "health burdens" Justice 40 threshold and our intensive margin measure of suppression effort could be indicative of tracts that are in a more urban environment, low in wildfire hazard potential. If so, these tracts would be less likely to be candidates for a retardant drop as it would be less likely they'd occupy space in the fire-prone WUI. It's also possible that this measure could be co-linear with traffic proximity, evidence suggests that road density is correlated with asthma (Salam, Islam, and Gilliland 2008). The final negative intensive margin coefficient for the Justice 40 thresholds is on the "housing" category[39]. It is explicitly stated that a

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[39] We don't find a negative coefficient for the correlation with the magnitude of LAT drops, but we did for the dependent variable model estimating the correlation with total LAT expenses.

census tract can qualify for this threshold if it is above the 90th percentile in lack of green space, so this coefficient may be a function of a reduced wildfire risk due to fewer/less dense vegetative fuels.

The goal of the Justice 40 initiative is to re-distribute federal investment in certain projects[40] with a more equitable share toward disadvantaged communities that are marginalized, underserved, and overburdened by pollution (White House 2022). Wildfire suppression resources are not covered under the initiative, despite resources like LATs representing a significant expenditure (Stonesifer, Calkin, Thompson, and Belval 2021). It's important to understand the fairness of investment in wildfire mitigation, especially without a formal system in place to ensure traditionally disadvantaged communities aren't under-allocated an environmental public good like wildfire suppression. Our research shows that, at the census tract and incident level, there was not an inequitable assignment of resources on the basis of being either (i) environmentally disadvantaged[41] or (ii) socioeconomically disadvantaged.

Without any other information, one could naively conclude that there is no inequity in wildfire management across race, income, or age. However, Anderson, Plantinga, and Wibbenmeyer 2023 show that certain communities are less likely to be the target of fuel reduction projects, meaning they could disproportionately be exposed to wildfire hazard. That minimizes our ability to claim that wildfire resources are allocated equitably when hazard potential might be distributed inequitably. This is important to note because it means that our control set may not allow us to account for inequities on these types of margins. We find no evidence of distributive inequity in the allocation of firefighting resources, but our analysis doesn't account for the potential of procedural injustice. It's possible that a positive feedback loop could be developed that continuously exposes communities with a lower socioeconomic status to more risk if we don't consider the equity of

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[40] The categories of the investments covered by the Justice 40 Initiative are the same as the Justice 40 criterion, except for "health burdens".

[41] While we did estimate a correlation between Justice 40 designation and the probability of receiving a drop that was statistically significant, we also found it to be positive, therefore not indicative of inequitably allocated aviation to underserved communities.

resource allocations over the entire life cycle of a wildfire (pre-ignition, initial attack, incident recovery, etc.).

A landslide federal court case in the state of Montana in 2023 raised the public's awareness of the adverse environmental effects of wildfire retardant, particularly to water (Mindock 2023). Some previous research has shown that retardant has minimal influence on the natural capital of the land it's employed on (Crouch et al. 2006a). Other evidence shows that wildfire retardant not only has an impact on the environment but also may taint the breathable air supply of those near the fire (Kalabokidis 2000). It would be wrong to assume that a retardant drop from a LAT solely provides benefits to the people receiving protection; they come with environmental and economic costs as well. It's possible that land managers could dispatch more hands-on suppression resources to protect higher-value homes if they were trying to avoid burdening them with the adverse effects of retardant.

Our results do not indicate that the federal government is overburdening disadvantaged people with retardant. Table 2.1 shows a positive coefficient on the extensive margin relationship with the low-income resident share; it also suggests a positive relationship with median income. The only minority group that appeared to disproportionately receive LAT suppression were Asian residents on the extensive margin. We may not be able to explicitly state that the allocation of LAT suppression effort is "equitable"; broadly, we do not observe evidence of inequity on the dimension of its benefits nor its costs.

The results of our analysis only equip us to speak to any inequity in the quantity of aviation effort applied to a community based on demographic factors. We are unable to detect if there could be an inequitable allocation based on the quality of resource assignments or effort applied[42]. Therefore, our measure of aviation suppression cannot be considered a complete measure of "effort". Additional work by researchers on the environmental justice of wildfire response should

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[42] Previous research has shown that there can be social heterogeneity in preferences toward wildfire prevention (Varela, Jacobsen, and Soliño 2014). Assuming this is true for wildfire suppression as well, it's also possible that "environmentally disadvantaged" communities could be recipients of suppression effort from sources that they hold a lower preference for.

focus on the allocation of other resources, such as helicopters, hand crews, or engines. Future iterations of our work will utilize more years of data and will ideally include information on aviation managed by other states as well.

2.5 Conclusion

Current federal initiatives seek to identify environmental injustices and rectify them through public investment. For example, the Justice 40 Initiative identifies tracts that are socioeconomically *and* environmentally disadvantaged, then commits to allocating 40% of all federal investments for climate change adaptation to these communities. We contribute to the emerging literature on the equitable allocation of resources to help communities cope with natural hazards like wildfire. Our research provides several contributions to the literature. First, we add more insight to pre-existing research on the determinants of wildfire suppression resource allocations (Bayham and Yoder 2020; Bayham, Belval, et al. 2020), especially work on understanding non-biophysical factors related to resource assignments and suppression strategies (Donovan, Prestemon, and K. Gebert 2011; Wibbenmeyer, Hand, et al. 2013; Rossi, Kuusela, and C. Dunn 2022). Second, we contribute to a much broader body of literature in environmental justice (Miranda et al. 2011; Harrison 2011; Masri, LeBrón, et al. 2021; Lathwal, Vaishnav, and Morgan 2022); specifically research on the equity of disaster resilience (Chakraborty, Collins, and Grineski 2019; Morse 2008). Finally, while there is existing work on the environmental justice of wildfire risk distribution (Masri, Scaduto, et al. 2021; Wibbenmeyer and Robertson 2022; Anderson, Plantinga, and Wibbenmeyer 2022), we are the first to evaluate the equity of public aviation expenditures on the application of effort to mitigate the damages borne from an ongoing disaster.

Using data on wildfires and large airtanker (LAT) allocations for wildfire suppression from 2017 to 2020, along with demographic information at the census tract level, we investigate whether the use of LATs systematically differs across communities based on socioeconomic and demographic characteristics. First, we compare fire-affected census tracts that do and do not receive LAT drops and find that census tracts that do not receive aviation have a higher percentage of minorities and residents over 64, while the tracts that receive aviation tend to have a higher share of low-income residents. However, these differences fade once we control for topographic and environmental characteristics that are known to influence wildfire behavior and this suppression effort. We also find that there is little heterogeneity in these findings based on race. However, we do find heterogeneity in the relationship between disadvantaged tracts and the suppression effort they receive from LATs based on the disadvantaged threshold that they exceed to earn the designation.

There are several important implications to come from our work. First, the “environmentally disadvantaged community” designation is not intended to be used for emergency response but rather a tool for allocating money as a part of a deliberative planning process. Our research supports this practice, as we don’t estimate an inequitable allocation for census tracts that are environmentally or socioeconomically disadvantaged. Secondly, this research needs to be paired with an understanding of how efforts to reduce damages prior to the wildfire, such as vegetative fuel reduction projects, are being equitably distributed. While we didn’t find that suppression resources are allocated differently to communities on the basis of factors like race or income, we can’t be sure that always remains the case if inequity in wildfire damage mitigation is creating a positive feedback loop with wildfire exposure. Finally, we believe this work will help inform policy aimed at bolstering efficiency in wildfire response, such as the Potential Operational Delineations (PODs) project (Calkin and C. O’Connor 2022) or resource prioritization guidelines.

Chapter 3

Managing Disaster Under Pressure: Estimating the Impact of Media Attention on Wildfire Suppression

Abstract:

The intensity and size of wildfires has grown in the United States over the last several decades, leading to higher suppression costs and increased concerns about the economic efficiency of resource allocation and the sustainability of firefighting budgets. Wildfire is a highly salient natural disaster, drawing the attention of the media and public at large. The objective of this study is to evaluate if the media's attention to wildfire exacerbates the costs of incident management through increased production of suppression effort. I build a novel daily panel dataset that contains daily firefighting expenditures, the amount of aviation used on a wildfire in a given day, and measures of online and television media attention. I use a two-stage least squares (2SLS) econometric approach to causally identify the impact of media attention on suppression decisions, instrumenting with the occurrence of independent news stories that draw attention away from wildfire. In contrast to existing literature, I find that the degree of media attention has no discernible impact on suppression decisions or expenditures.

3.1 Introduction

The sharp increase in the cost of controlling wildfires is a result of the rapid growth in severe wildfire incidents (NIFC 2023). The federal government spent over $4 billion in a single year on wildfire suppression for the first time in 2021. The federal government currently manages a stock of resources to fight these fires with constraints that are often binding (Thompson, Belval, et al. 2023). The supply of wildland firefighters has diminished in recent years (Belval, Bayham, and Magstadt 2024), despite the growth in wildfire damages and limited resources available.

Wildfire is a highly salient natural disaster that draws the attention of the media and the general public. We need to understand if the increased attention to certain wildfires leads to a misallocation of suppression funds. If so, then fires that require more critical intervention may not receive the firefighting resources they need, given the tight resource constraints that land managers face.

The objective of this study is to investigate if attention from the media to wildfire influences suppression decisions. I combine daily information on aerial suppression, firefighting costs, and measures of media attention to create a unique panel dataset for this analysis. It is implausible to expect that there will only be a direct causal relationship between media attention and firefighting decisions; there is likely simultaneity where firefighting decisions affect the degree of media attention. Therefore, I use a two-stage least squares (2SLS) econometric approach where the occurrence of different catastrophic news stories instruments for the impact of media attention.

I find a negative first-stage effect on the impact of a catastrophic event on public attention. My second-stage results do not indicate that media attention is an important determinant of wildfire resource allocations.

3.2 Background

Most research on the topic of wildfire resource demand has focused on the role that biophysical factors play in a suppression strategy. The size of the wildfire (Hand, K. M. Gebert, et al. 2014; Thompson, Calkin, Herynk, et al. 2013) and the number of threatened structures (Bayham and Yoder 2020; Baylis and Boomhower 2019) are primary determinants of the suppression resources provided to a fire. Weather is another important driver of resource allocations (Bayham, Belval, et al. 2020). We have evidence that there are some non-biophysical factors that influence suppression strategy, such as risk perceptions (Hand, Katuwal, et al. 2017; Hand, Wibbenmeyer, et al. 2015). Psychological biases could influence the allocations of suppression resources by incident management (Thompson 2014). Resource over-allocations from "human" factors create a high potential for positive feedback loops, increasing suppression expenditures even further in the long-run (Calkin, Thompson, and Finney 2015).

Researchers in the social sciences have investigated the influence that media attention can have on different outcomes. Some have found media to have a profound influence on human behavior. Jetter 2014 takes an instrumental variable approach to find that media reporting on terrorism increases the occurrence of terrorism. Other researchers have found media to only have a mild effect on outcomes; there's been almost no impact on the price of Bitcoin from media attention (Philippas et al. 2019). There's also evidence that the effect of media attention is highly context-dependent; some respond strongly to negative scrutiny when they wouldn't at all to positive attention (An et al. 2022).

I am not the first to ask how the attention of the media to wildfire influences incident management. Donovan, Prestemon, and K. Gebert 2011 estimates how much the media coverage or the political pressure on a wildfire incident influences suppression costs. They use an instrumental variable approach to show that media attention increases suppression expenditures. However, they rely on a strong assumption of the exclusion restriction with their instrument, the distance from a fire's ignition to the city of newspaper coverage. I improve upon their approach by constructing a novel instrument that meets the exclusion restriction. I also build upon their analysis by leveraging data with finer temporal resolution. The additional time dimension highlights the dynamic effects of media on wildfire suppression.

I contribute to the literature on wildfire management in several ways. First, I provide causal estimates on the impact of media pressure on wildfire suppression decisions. Second, I contribute to the broad literature on the drivers of resource demand for wildfires (Belval, Wei, et al. 2017; Bayham and Yoder 2020; Hand, Katuwal, et al. 2017), especially with respect to the human decision-making element. Third, my analysis improves upon previous work on the relationship between wildfire and the media by using measures of television and internet media attention[43]. Finally, this work provides an example of a credible estimation strategy for identifying the impact of media attention on a particular event, given standard instrumental variable assumptions (Labrecque and Swanson 2018).

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[43] Donovan, Prestemon, and K. Gebert 2011 focused on the impact of print media on suppression costs.

The rest of the paper will be organized in the following way. In Section 2, I explain my conceptual framework, including a brief literature review on IV methods and their assumptions. I also present my econometric specification and the data source for all the variables used in my analysis. Section 3 shows results from the two-staged least squares estimation of the impact of media attention on wildfire. In Section 4, I explore the significance and broader relevance of my findings. Concluding remarks and policy implications are discussed in Section 5.

3.3 Methods

This section outlines the approach taken to investigate the relationship between media attention and wildfire suppression decisions. Media attention might influence suppression strategy and vice versa, due to simultaneity, so a standard linear regression model could produce biased results. To address this challenge, I employ a two-stage least squares (2SLS) estimation strategy, using catastrophic events that distract the media's attention as an instrumental variable (IV) to isolate exogenous variation. This approach allows me to estimate the causal impact of media attention on suppression strategy more accurately.

The analysis is grounded in a conceptual framework that models the decision-making process of federal land managers, who balance suppression costs against wildfire damages while being influenced by external factors. This framework employs a novel panel dataset that combines daily incident-level suppression data with state-level media attention metrics, controlling for key bio-physical and economic factors. The following subsections provide a detailed explanation of the conceptual framework, data sources, and econometric methods employed in this study.

3.3.1 Conceptual Framework

The primary challenge with estimating the impact of media attention on incident management is the simultaneity in their relationship. How can we be certain that the actions taken by wildfire managers aren't attracting the attention of the media? This simultaneity could bias the results of a standard linear regression of suppression decisions on media attention, inflating the magnitude of coefficient estimates and overstating the effect of media attention. Instrumental variable estimation is one way to circumvent the simultaneity issue (Heckman 1996). In this section, I explain the economic theory underpinning the potential relationship between media attention and wildfire suppression strategy. Then, I discuss my strategy to obtain causal estimates for the impact of media attention using a two-staged least squares approach, including my choice of instrument.

The federal government uses a multi-tiered system to make resource allocations and suppression decisions over the course of a fire season. Incident management makes requests for resources (hand crews, fire engines, large airtankers, helicopters, etc.) needed on a fire based on current and expected fire conditions. Their goal is to minimize damages from the wildfire to people, structures, or other valued assets. These requests are taken to the regional land management agency and generally granted unless resource constraints are binding at the time. The incident management team will then assign different tasks to a resource once it has been dispatched to a wildfire.

After a resource is dispatched to a wildfire, incident management decides where it will be used and how much it will be used. Biophysical conditions and resource availability are the main factors in these allocations (Hand, K. M. Gebert, et al. 2014). Studies have shown there to be a distinct human element to suppression strategy (Thompson 2014); this creates a channel for several factors to influence suppression strategy. Economic theory is theoretically ambiguous about the direction of media attention's impact on suppression decisions. The media's focus could cause land managers to be more conservative with their use of an expensive public good, like aerial suppression, out of fear that it might draw more scrutiny (Cuadrado-Ballesteros, Frías-Aceituno, and Martínez-Ferrero 2014). However, media attention on an incident could motivate incident management to be more aggressive in their suppression strategy by assuaging the negative externalities[44] from those decisions (Pan, Diao, and L. Wang 2023).

Media attention could influence the suppression decisions of a wildfire through several different points in an incident's chain of command. I conduct this analysis at the fire level rather than at

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[44] For example, the media could help mitigate negative attention from the public for using suppression techniques that pollute the environment, like LAT retardant (Kalabokidis 2000).

a regional scale, as incident management teams have the greatest influence over daily suppression strategy on a wildfire. They are the party most likely to have decisions influenced by the scrutiny of wildfire by the media. It is less plausible, for example, that a hot shot crew would have their suppression activity influenced by media attention. The press might have an influence on the decisions of the regional coordinator, but that would likely only change how resources are dispatched across wildfires, not how they are used within fire.

I build off of the canonical C + NVC model (Simard 1976; Donovan and Rideout 2003; Rossi and Kuusela 2019) for my research question, adapting it to the incident manager's choice of a level of wildfire suppression:

$$\text{Min} \quad L(S) = \theta_1 S + NVC(S) \tag{3.1}$$

The goal for the incident manager is to minimize the sum of costs and net damages from wildfire. Suppression resources *S* reduce wildfire damages on an active incident. θ_1 is the per-unit resource cost of suppression. Net damages *NVC* are a function of the suppression resources allocated.

Equation 1 models how much suppression to use on a wildfire if the decision was made by the benevolent social planner only concerned with costs and damages. I model the decision of how much suppression to use on a wildfire with incident manager incentives:

$$\text{Min} \quad L(S) = \theta_1 S + NVC(S) + \Gamma(NVC(S), \Omega) \tag{3.2}$$

Incident manager incentives are represented as Γ. Those incentives will be a function of the net damages from the wildfire, as they will have an impact on an incident manager's professional reputation. Wildfire media attention is represented as Ω, an external factor that could influence an incident manager's decisions. In Equation 2, the only way that media attention could influence suppression decisions is through the manager's incentives[45].

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[45] This analysis models only media attention and changes in net damages through Γ for simplicity's sake. Other factors, such as overtime pay or political influence, could also be a part of an incident manager's incentives.

When we take the first-order conditions with regard to S, we obtain the incident manager's policy function:

$$(1+\frac{\partial \Gamma}{\partial NVC})*\frac{\partial NVC(S)}{\partial S}=-\theta_1 \tag{3.3}$$

The left-hand side models the marginal benefit from a one-unit increase in suppression, represented as the marginal change in net damages and manager incentives. The right-hand side of the equation contains the marginal cost of an increase in suppression resources[46]. The incident manager will choose a level of suppression S^* that solves Equation 3.

We include the incident manager's decision of S^* in their objective function as follows:

$$\text{Min} \quad L(S^*)=\theta_1 S^*+NVC(S^*)+\Gamma(NVC(S^*),\Omega) \tag{3.4}$$

In this research, I evaluate whether S^* is a function of Ω (mediated by Γ). In a naive framework, we would only need to see that $\frac{\partial L(S^*)}{\partial \Omega} \neq 0$ to prove that suppression resources are a function of media attention. However, there is likely simultaneity between media attention and suppression decisions, as theorized in Donovan, Prestemon, and K. Gebert 2011.

I model the simultaneity between media attention and suppression in the incident manager's objective function as follows:

$$\text{Min} \quad L(S^*)=\theta_1 S^*+NVC(S^*)+\Gamma(NVC(S^*),\Omega(S^*)) \tag{3.5}$$

Wildfire suppression has a tendency to be highly salient at times and could attract the attention of the media or scrutiny of the general public. This simultaneity complicates the relationship, meaning I cannot simply estimate the impact of media attention through OLS. I must use a more sophisticated identification strategy that focuses on exogenous variation in media attention.

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[46] The sign on θ_1 is negative because the marginal benefit on the left-hand side will be a *reduction* in net damages.

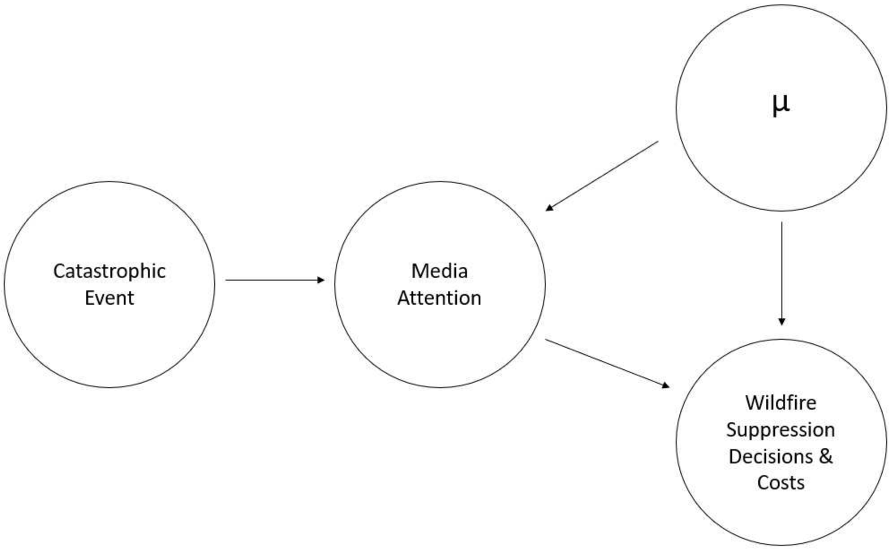

Figure 3.1: Directed acyclic graph (DAG) of the relationship between catastrophic events, media attention, and suppression decisions

Figure 3.1 provides a visual depiction of the hypothesized relationship between media attention and suppression strategy. As the figure shows, there are direct and indirect channels for simultaneity to take hold. First, increased (decreased) media attention could directly motivate incident managers to fight fire with more aggressive (conservative) tactics and result in an expansion (reduction) in the resources deployed. However, it's possible that more aggressive suppression strategies could also draw greater attention from the media. That would inflate coefficient estimates, leading one to deduce media attention media attention has a stronger effect than it actually does on suppression strategy.

There is also an indirect pathway for simultaneity to bias coefficient estimates (Marvell 2019). The term μ in Figure 3.1 will capture factors that influence wildfire management like severity or growth, factors that are also a determinant of the media attention going to wildfire. Intuitively, these wildfire-related factors are directly affected by suppression strategy. This opens another pathway for simultaneity to affect the relationship between media attention and suppression decisions. Media attention could influence incident managers to fight fire with more aggression, causing a reduction in wildfire growth. If the fire were to be less disastrous as a consequence of this, then incident managers could scale back resources. This indirect channel may lead us to understate the effect of media scrutiny on suppression decisions[47]. That is why a proper causal identification method is necessary to isolate the true effect of media on wildfire resource decisions.

Newsworthy events draw attention away from wildfire. I exploit the random occurrence and timing of these events to isolate the relationship between wildfire suppression decisions and media attention using IV regression. Media firms operate with resource constraints and finite capital. Theoretically, a highly salient news event like a mass shooting could crowd out the focus the media is devoting to wildfire as they divert resources toward coverage of the other event. This phenomenon creates an external source of variation in media attention devoted to wildfire, allowing us to circumvent the issue of reverse causality by using IV estimation. I believe this is a defensible approach because it meets the needs of the three main assumptions needed to use an IV estimator; the exogeneity condition, relevance condition, and the exclusion restriction.

The *exogeneity condition* states that the instrument must be randomly assigned to the outcome variable. The *relevance condition* states that the instrumental variable, mass shootings, must have an observable impact on the endogenous regressor, the media attention to wildfire. This means that the validity of this estimation strategy relies upon the occurrence of a mass shooting affecting media scrutiny of wildfire. I am able to test this assumption and find that my instrument has a clear impact on media attention with the expected (negative) sign[48]. Lastly, the *exclusion restriction* states that the instrument must not have any direct impacts on the outcome variable other than through the instrumented endogenous regressor. In the context of this research, that would mean a mass shooting has no impact on firefighting decisions other than through crowding out media attention.

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[47] It's important to point out that in my examples for the direct and indirect channels, I assume a positive relationship between media and firefighting. However, it's possible that incident managers could become more conservative with their suppression strategy as a consequence of media scrutiny, as pointed out in Cuadrado-Ballesteros, Frías-Aceituno, and Martínez-Ferrero 2014.

[48] The relationship between catastrophic events and measures of online media attention passes tests of instrument strength on most levels. The relationship between those events and TV media attention passes the same test(s) on every level.

Instrumental variable estimation allows us to estimate the average causal effect, referred to as the local average treatment effect (LATE), of the explanatory variable(s) on the outcome(s) of interest for a subset of "compliers" (Angrist and Imbens 1995). In the context of my research, the "compliers" will be the wildfires that observed a change in media coverage due to the occurrence of a catastrophic event. The LATE will, therefore, give the average impact on wildfire suppression decisions of a reduction in media coverage due to a catastrophic event. The LATE will not give us an estimate for the effect of media attention for *all* wildfires.

3.3.2 Data

A novel panel dataset is used for this analysis that combines daily information on firefighting suppression strategy measured at the incident-level and media attention to wildfire measured at the state-level. My source for media attention comes from GDELT (Leetaru and Schrodt 2013) and considers both internet and television news sources. I measure daily wildfire suppression strategy in two separate ways. First, as the amount of LAT suppression effort allocated using data on retardant drops from ATUs mounted inside the aircraft. Second, as the daily suppression expenses reported on the IC209 forms (St. Denis et al. 2023). I also include daily controls for (i) weather measured at the fire-level and (ii) preparedness, measured at the national- and regional-level[49].

If the public's attention to a wildfire does influence the incident management team's suppression strategy, that could result in changes in the type and amount of resources used. In this research, I focus on changes in the way aviation is used on the wildfire in question. I believe it is justifiable to focus on aviation as it's arguably the most costly active suppression strategy (Calkin, Stonesifer, et al. 2014), and I have high-quality data on its use by the federal government. The data I use to measure aviation use comes from Additional Telemetry Units (ATUs) mounted on large airtankers (LATs) that give information on when and where they are dropping fire retardant. These data measure the number of drops at the fire level made in suppression, how many gallons of fire retardant were delivered, and the number of different LATs used.

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[49] The federal government uses official wildfire "preparedness levels" to inform wildfire managers about firefighting resource availability and demand (Cullen, Axe, and Podschwit 2020).

My measure of media attention comes from the GDELT project, which monitors trends in both television and online news media. The data from GDELT provides a daily share of media coverage from a subset of online media outlets recorded on the Internet Archive (Leetaru and Schrodt 2013). I enter a query into their search engine in the format of “wildfire (STATE OF WILDFIRE)”. For example, with the 2017 Lolo Peak fire, I would have requested trends on “wildfire montana”. GDELT also manages network-level data on trends in television media attention. I obtain data on these trends for three national television media outlets: CNN, FOX News, and MSNBC. I then use this data on media attention at the state-level to construct one of my explanatory variables: a count for the number of national networks (1 - 3) with a story about a state’s wildfires.

I focus on the media attention dedicated to wildfires statewide for several reasons. The primary reason is for consistency in the data. Media outlets rarely share an incident number when reporting on wildfire, and only the largest and most threatening wildfires have a consistent naming convention across all stakeholders. Focusing on wildfire coverage at a coarser spatial scale will minimize measurement error. It’s further justified by the simple fact that each fire in my sample will contribute to the media’s interest in wildfire in its state. The national media dedicating more resources to cover Fire X will imply an increase in the national media resources used to cover wildfire in Fire X’s state.

Figure 3.2 displays a plot of the distribution of LAT suppression effort based on the national television coverage of wildfire. We can see that there are fewer days of firefighting when a national media outlet dedicates airtime to wildfires in the state. It’s also apparent that the days with the most aviation-intensive suppression occur when there is television media scrutiny. This may indicate a strong correlation between suppression effort and media coverage, unless the relationship is confounded by another factor, like weather.

I include variables in my data to ensure that I’m not biasing the relationship between the media’s attention to wildfire and suppression decisions. Those controls can be separated into two

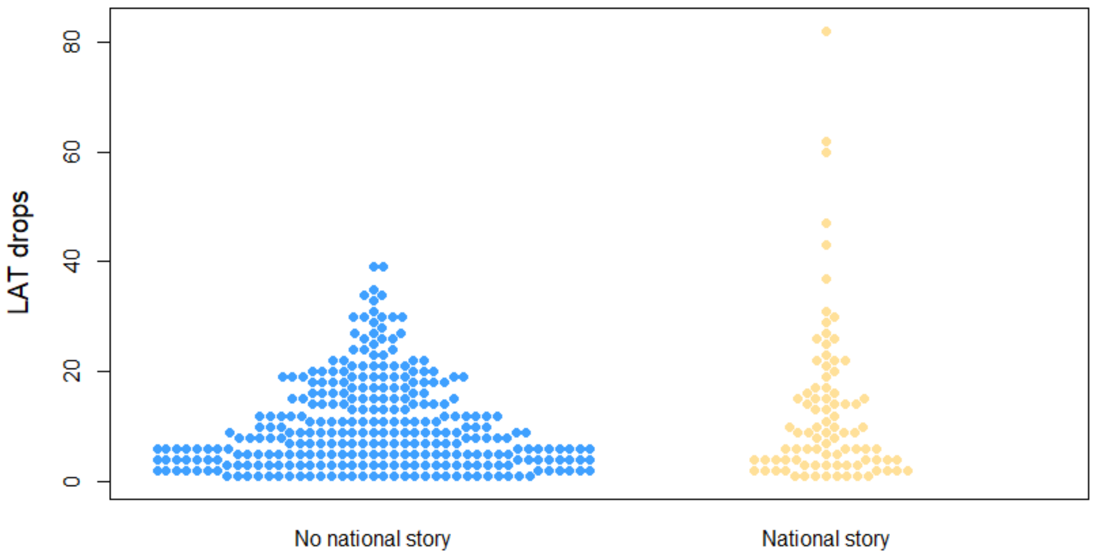

Figure 3.2: Beeswarm plot of the density and distribution of LAT retardant drops based on national TV coverage of wildfire.

distinct categories: weather and preparedness. The weather variables; precipitation, vapor pressure deficit, wind speed, and temperature; are obtained from Gridmet (Abatzoglou 2013). I extract an area-weighted daily measure for each weather variable using the final fire perimeter from Monitoring Trends in Burn Severity (MTBS), then include that in the daily panel.

I use daily information on preparedness from the USFS to get a sense of resource demand on any given date. This data contains information on the number of fires currently engaged in suppression (nationwide and regionally), the number of complex incident management teams deployed, and a general preparedness level (1 -5) measured nationwide and regionally (IMSR 2023). This information will account for an incident's decreased (increased) likelihood of receiving the resources that they request on days when there is more (less) competition for firefighting resources.

Table B1 (see Appendix) contains a list of different events that distracted the media's attention at different points in time during my sample period. I choose to focus on shooting incidents that resulted in 10+ deaths, as well as two other highly salient and exogenous events that were domestic to the US. Treatment by my instrument is defined as all days of firefighting that occur over the week that follows one of these events. I do this because these events tend to draw media attention for at least a week, evidenced by Figure 3.4. This also allows me to account for trends in the weekly news cycle and thus how media resources are allocated; every fire that is active during a catastrophic event has five weekdays of "distraction" and two weekend days[50].

Figure 3.4 shows trends in the coverage of catastrophic events in the media. Immediately following the occurrence of a catastrophic event, there's a sharp rise in the amount of media attention devoted to that event. This lends further credence to the exogeneity condition[51], as it is unlikely the media is planning wildfire coverage around these events. Figure 3.4 also shows trends in the coverage of the 2018 Camp fire in California. The Camp fire evolved very quickly in its early hours to become one of the most severe and deadly wildfires in US history (Brewer and Clements 2019). Despite the rapid early growth, there was not a similar rise in coverage of the fire as we see with mass shootings. This reinforces my instrument; media coverage of mass shootings rapidly increases in a way that is distinct from other events like wildfire, further supporting the validity of the exogeneity condition.

I build the data set for this analysis by first measuring media attention for every day from January 1, 2017 to March 2020[52]. The data is then subset twice for each fire in my panel to get the sample I use to produce estimates. First, I keep only the days for each fire that span from its ignition date to its official "control" date. Figure 3.3 displays a plot of the density of online and television media attention (from GDELT) and LAT drops in our sample over the duration of a suppression campaign; it is clear that both aviation and the media are more active at the beginning of an incident. Because of that, I subset the data again to just the first 25% of firefighting days in a suppression campaign, leaving me with 4,336 days of firefighting across 265 wildfires.

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[50] Unless, of course, it is contained or controlled prior to the end of the week.

[51] See Figure B1 in the Appendix for further evidence of the exogeneity condition. The plot shows that there is minimal correlation between the second stage regression in my model and the occurrence of catastrophic events.

[52] There were a few fires in my sample that observed an ignition in 2019 that burned into 2020. I build my panel that far out to account for these fires.

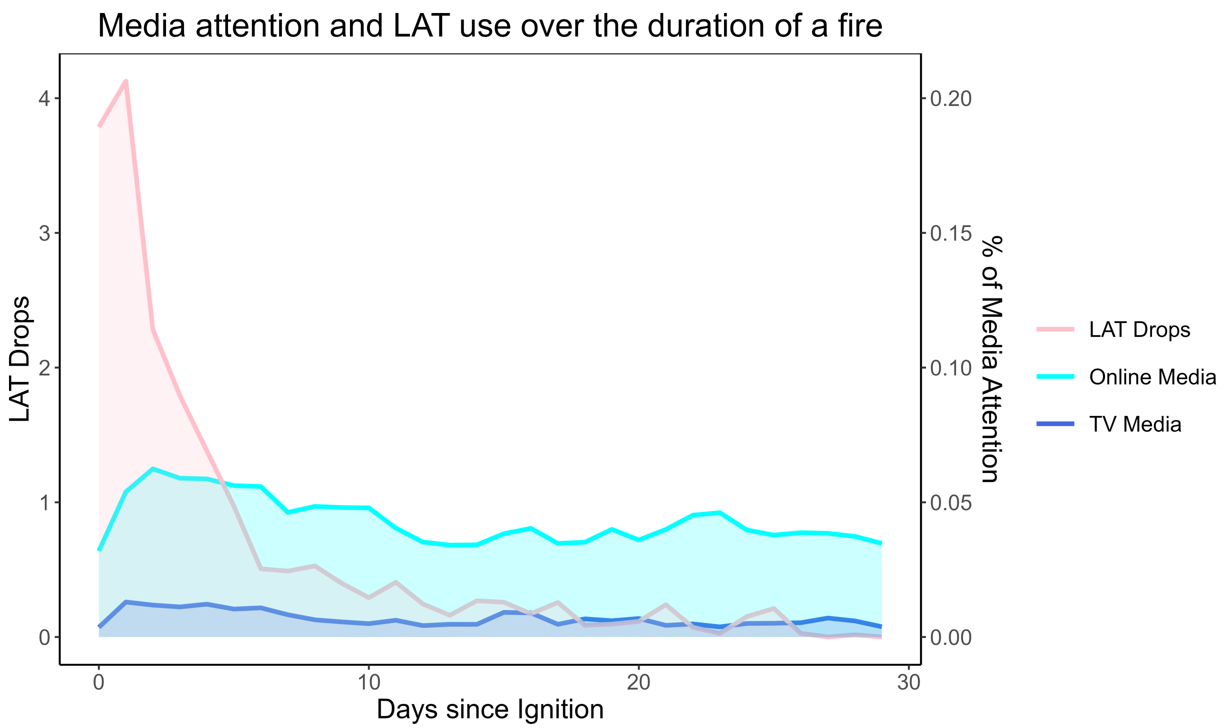

Figure 3.3: Trends in internet/TV media attention to wildfire (state-wide) and suppression decisions over the duration of a wildfire's burn.

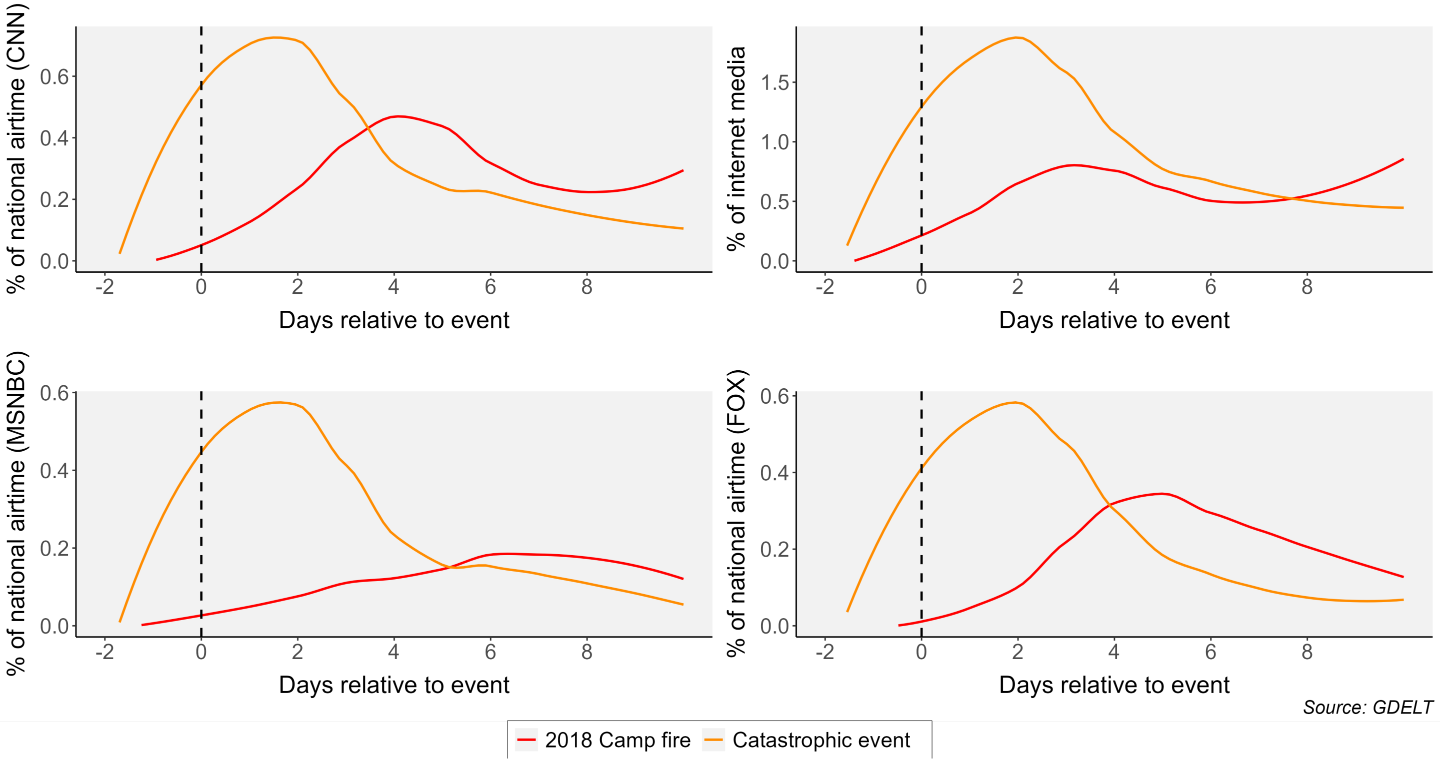

Figure 3.4: Trends[53] in media coverage of catastrophic events compared to the 2018 Camp fire

Table 3.1 contains summary statistics for the important variables in our analysis at the fire & day level. On the average firefighting day in our sample, there are 1.01 drops of retardant released and \$344,250 in suppression expenditures. 0.05% of internet media attention is devoted to wildfires (state-wide). Eleven percent of firefighting days observe a national news segment about wildfires in-state. Four percent of firefighting days in my sample occur during a week of media fallout from a catastrophic shooting. That increases to about eight percent of firefighting days when including all events featured in Table B1.

Table 3.1: Summary statistics for primary variables

	Variable	Mean	Std. Dev.	Min	Max.
Key variables					
	Total LAT Drops	1.01	4.35	0	82
	Total LATs	0.25	0.69	0	8
	Suppression Expenditures (\$1000s)	344.25	2355.20	0	112750
	Share of all online media (statewide)	0.05	0.11	0.01	1.72
	Any national news story about state's fires (binary)	0.11	0.31	0.00	1.00
	Week of mass shooting (binary)	0.03	0.18	0.00	1.00
	Week of "media distraction" (binary)	0.08	0.27	0.00	1.00
Controls					
	Max. Temperature (C)	27.84	5.93	28.40	44
	Wind Speed (m/s)	3.23	1.21	3.00	13.07
	Vapor Pressure Deficit	1.70	0.72	1.64	4.61
	Precipitation (mm)	0.56	2.25	0.00	48.32
	National preparedness level (1-5)	3.71	1.33	4.00	5
	Regional preparedness level (1-5)	2.94	1.56	3	5
	New ignitions (national)	127.23	60.34	119.00	901
	New ignitions (GACC-level)	16.82	15.29	14.00	155
	Type 1 IMTs Committed	6.70	4.90	5	17
	Days since ignition	13.94	14.90	10	116
	Observations	4336			

Table B2 describes the different fires we use in this analysis across the entire duration of their burn. As you can see, on average, there are a little over four airplane-days[54] of LAT aviation used on each fire. 63% of the wildfires in my sample received suppression from a LAT. The average fire in the sample receives just under twenty-four drops from a LAT. 4% of the fires in our sample observe a mass shooting occurrence during one of their suppression days; 8% of them observe an occurrence of any event from Table B1. In our sample, the average fire observes 0.13% of total internet media attention going to wildfire (state-wide) on the peak day of coverage. The most attention to wildfire that any incident in my sample observes is the Camp fire (CA) when 1.72% of all internet media covered fire in California on Nov. 10, 2018. 12% of the fires in my sample observed a national story about wildfire in its state at some point during its burn.

3.3.3 Econometric Specification

The goal of this research is to estimate the impact of media attention on wildfire suppression decisions. In the absence of any concerns of simultaneity bias (see Equation 3 of the Conceptual Framework), I would employ the following econometric specification:

$$SD_{it} = \beta_1 \text{Media}_{st} + \beta_2 W_{it} + \beta_3 E_{it} + \gamma_r + \rho_i + \psi_t + \mu_{it}$$

Our outcome variable, SD_{it}, represents the suppression decisions made on the t^{th} day of suppression of wildfire *i*. Aerial suppression effort allocations are the focus of this analysis, as I am mostly interested in determining if media attention causes changes in measurable resource decisions. I also consider the impact on suppression expenses. The impact of media attention on these dependent variables is measured both contemporaneously and projecting forward, in case the media's attention influences decision-making for more than one day.

The explanatory variable, Media_{st}, represents the media coverage of wildfire in state *s* on day *t*. GDELT provides two separate measures we use as a proxy for the degree of media attention

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[54] By "airplane-days", I mean the total number of flight days across all aircraft. For example, if a fire used three LATs to fight fire for two days each, that would be six airplane-days. If one aircraft was used for five days, while two others were used for a day each, that would be seven airplane-days.

received by wildfire in a state. The first is a variable representing the share of all online news stories on day *t* devoted to wildfires in the state s that wildfire *i* is burning. The second is a count of the major networks (CNN, MSNBC, or Fox News) on day *t* with a segment on wildfires in state s. This measure of media attention only varies by state, so standard errors are clustered at the state-level.

W_{it} contains a vector of controls for the weather on fire *i* and day *t*. The variables included in this vector are controls for the daily weather on the fire; vapor pressure deficit, precipitation, temperature, and wind speed. The vector E_{it} contains controls for suppression strategy constraints. These are controls for the Forest Service's general level of preparedness to suppress new fires, the number of other fires currently burning on day *t*, and the number of complex incident management teams committed. There are also variables included for these factors at the local level. γ_r is a GACC-level fixed effect, controlling for any time-invariant heterogeneity in wildfire suppression strategy or resource allocations at the regional level. ρ_i is an incident-level fixed effect; this will capture any time-invariant heterogeneity such as topography, vegetation, or proximity to homes/neighborhoods. In the full specification ψ_t, a day-of-incident fixed effect, is included to account for temporal patterns across all wildfires in suppression strategy and media coverage.

Due to concerns of simultaneity bias between the degree of media attention on a wildfire and the suppression strategy used, OLS would introduce biased estimates for the impact of media attention, likely overstating its importance. I use a two-stage least squares estimation model where the occurrence of a disastrous event on day *t*, such as a mass shooting, instruments for the degree of media attention. The econometric specification I use to estimate the impact of media attention takes the following two-stage form:

$$\hat{\text{Media}}_{it} = \beta_1 \text{Catastrophic Event}_{it} + \beta_2 W_{it} + \beta_3 E_{it} + \gamma_r + \rho_i + \psi_t + \mu_{it} \tag{3.6}$$

$$SD_{it} = \alpha_1 \hat{\text{Media}}_{it} + \alpha_2 W_{it} + \alpha_3 E_{it} + \gamma_r + \rho_i + \psi_t + \epsilon_{it} \tag{3.7}$$

Equation 7 represents the second stage of my model, where I estimate the effect that media attention, Media_{it} has on the suppression decisions of wildfire i's t^{th} day of suppression, SD_{it}. I use the same set of controls as described in Equation 5.

Equation 6 represents the first stage of my 2SLS model, where I estimate the effect that the occurrence of a catastrophic event, $\text{Catastrophic Event}_{it}$, can have on the media attention, Media_{it}, devoted to a wildfire. The same set of controls is used in the first stage of the model as the second.

3.4 Results

3.4.1 Main results

The main concern with any simple estimation of the relationship between media attention and wildfire suppression is simultaneity. A more aggressive suppression strategy could influence more media coverage of wildfire, overstating the effect of media on wildfire management. The top panel of Table 3.2 shows coefficient estimates and standard errors from a traditional OLS regression of aerial suppression effort on different measures of media attention. I find a statistically significant and positive relationship with both measures of media attention; the share of total internet media attention directed at wildfire and the count of national TV media outlets (MSNBC, CNN, or Fox News) with a segment on wildfires in a particular state. The coefficient estimates from the naive model that uses the full set of controls suggest that a one percentage point increase in the share of total internet media attention to wildfire would correspond to 1.8 additional retardant drops on wildfires in that state. An additional national television network dedicating airtime to wildfires would lead to approximately 0.74 more retardant drops on wildfires within the state being covered.

Table 3.3 shows coefficient estimates and standard errors for the model repeated with daily suppression expenditures as the dependent variable. Both measures of media attention appear to have a significant effect on firefighting costs. The coefficient estimates from the full naive model suggest that a one percent increase in the total media attention to wildfire would increase suppression expenditures by nearly \$2 million dollars on that day. Similarly, an additional television

Table 3.2: OLS regression of media attention on LAT suppression effort allocations.

Contemporaneous	(1) LAT drops	(2) LAT drops	(3) LAT drops	(4) LAT drops
% of internet media	5.578***	4.934***	2.536***	1.778***
	(0.642)	(0.378)	(0.312)	(0.161)
Count of TV networks	3.165***	2.678***	1.133***	0.746**
	(0.204)	(0.142)	(0.317)	(0.302)
Weather controls	No	Yes	Yes	Yes
Preparedness controls	No	Yes	Yes	Yes
Incident F.E.	No	No	Yes	Yes
Day-of-incident F.E.	No	No	No	Yes
GACC F.E.	No	No	No	Yes
Observations	4,336	4,336	4,321	4,138

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the state level in parentheses.

Each coefficient estimate comes from its own regression.

network covering wildfire would result in an additional $209,000 in expenditures, according to naive estimates.

Instruments must meet the "relevance condition" in order to be valid for two-stage least squares estimation. This means that catastrophic events must have an effect on the attention going to wildfire in-state. I can test for the relevance condition by deriving coefficient estimates to verify a statistical relationship. Table 3.4 shows the coefficient estimates for the first stage of my two-stage least squares (2SLS) specification. The top panel contains coefficient estimates for the impact of a catastrophic event on the share of total internet media attention going to wildfire in a state; the bottom panel contains results for its impact on the count of national television networks reporting on wildfire in a state. The negative sign on the coefficients for both measures of media attention confirms my hypothesis: catastrophic events crowd out the amount of media coverage dedicated to wildfires. According to the coefficients in Column 4, catastrophic events reduce the total internet media attention going to wildfire in a state by 0.02% and lead to 0.1 fewer national TV networks with a segment on the state's wildfires.

Table 3.4 confirms a statistical relationship between my instrument and the endogenous media attention variables, but in order to fully suffice the "relevance condition", I must show that the instrument has requisite strength. Table 3.5 shows the F-statistics for each model estimation

Table 3.3: OLS regression of media attention on suppression costs.

Contemporaneous	(1) Dollars ($1000s)	(2) Dollars ($1000s)	(3) Dollars ($1000s)	(4) Dollars ($1000s)
% of internet media	3173.803***	3085.159***	1867.525***	1950.731***
	(257.078)	(274.655)	(364.474)	(394.143)
Count of TV networks	537.499***	516.525***	175.602	209.899*
	(76.851)	(45.160)	(111.005)	(109.530)
Weather controls	No	Yes	Yes	Yes
Preparedness controls	No	Yes	Yes	Yes
Incident F.E.	No	No	Yes	Yes
Day-of-incident F.E.	No	No	No	Yes
GACC F.E.	No	No	No	Yes
Observations	4,336	4,336	4,321	4,138

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the state level in parentheses.

Each coefficient estimate comes from its own regression.

Table 3.4: First stage: Impact of a catastrophic event on the media coverage of wildfire.

Media measure #1	(1) % of internet media attention	(2) % of internet media attention	(3) % of internet media attention	(4) % of internet media attention
Catastrophic event	-0.010	0.004	-0.019**	-0.022***
	(0.008)	(0.014)	(0.006)	(0.005)
Media measure #2	Count of TV networks	Count of TV networks	Count of TV networks	Count of TV networks
Catastrophic event	-0.089**	-0.035	-0.085***	-0.105***
	(0.032)	(0.029)	(0.024)	(0.018)
Weather controls	No	Yes	Yes	Yes
Preparedness controls	No	Yes	Yes	Yes
Incident F.E.	No	No	Yes	Yes
Day-of-incident F.E.	No	No	No	Yes
GACC F.E.	No	No	No	Yes
Observations	4,336	4,336	4,321	4,138

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the state level in parentheses.

Each coefficient estimate comes from its own regression.

presented in Table 3.4. I estimate these F-statistics using the Montiel-Pflueger test for weak instruments (Olea and Pflueger 2013), a method for evaluating instrument strength that is robust to autocorrelation, clustering, and heteroscedasticity. The test assesses a null hypothesis that IV estimates would introduce a specific percentage of the bias that would occur with OLS.

The effective F-statistics derived in Table 3.5 indicate that catastrophic events will satisfy the "relevance condition" needed for 2SLS estimation in my full specification. We cannot reject the hypothesis that the instrument would remove bias in a model with no other controls or fixed effects, according to Column 1. The F-statistics in Column 2 show that the inclusion of an incident fixed effect in the model allows us to reject the null hypothesis. Specifically, we can reject a hypothesis that instrumenting for the impact of television coverage introduces more than 20% of the bias that OLS would. We cannot draw any conclusions about the ability of my instrument to remove bias from the other two measures of media attention in models with incident fixed effects, but no controls.

In the full model, displayed in Column 4, the derived effective F-statistics indicate varying levels of instrument strength in removing bias from both measures of media attention. An effective F-statistic of 18.54 allows us to reject the null hypothesis that instrumenting for the impact of online media attention with catastrophic events would introduce more than 20% bias compared to OLS[55]. A value of 35.38 for the count of national networks means we can reject the null that there will be up to 10% of the bias of OLS.

Now that the relevance condition has been proven, I can use exogenous variation in wildfire media attention from the occurrence of catastrophic events to determine its impact on suppression decisions. Table 3.6 shows coefficient estimates and standard errors for the second stage of my 2SLS model. The top panel contains results for the impact of media attention on the number of LAT drops on the same day. There appears to be a positive sign for the impact of both types

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[55] I elect to report the more conservative estimate of my instrument's strength using a test robust to clustering standard errors. Using the method presented by Stock and Yogo 2005 would allow me to claim an even stronger instrument, as I would reject a null hypothesis that the instrument allows more than 10% of the bias of OLS.

Table 3.5: Effective F-statistics for first-stage regression of media attention on catastrophic event occurrences

	(1) No controls, no fixed effects	(2) No controls, incident F.E.	(3) Full controls, incident F.E.	(4) Full controls, all F.E.
Share of total internet media attention to state's wildfires	1.31	6.55	9.17	18.54
Count of national TV networks with a story about state's wildfires	7.87	8.65	12.36	35.38

of media (internet and television) on aerial firefighting output, but not statistically significant for either measure.

Media attention may not influence suppression decisions contemporaneously. It might instead affect the decisions of wildfire management over the next few days[56]. Because of this, I also model the impact of internet and TV media attention on LAT drops over the next three days (second panel) and seven days (third panel). I do not find a statistically significant effect on aerial fire suppression for internet or TV media attention over either period of time.

I didn't find media attention to have an influence on the amount of aviation used to fight wildfire, but it could still impact firefighting expenditures through other resource decisions. Table 3.7 shows the second stage results for a model using daily suppression costs as the dependent variable. I don't find a significant relationship between the measures of wildfire media attention and same-day suppression costs. Similar to Table 3.7, I also present coefficients for the relationship between media attention and suppression expenditures over the next three and seven days. My results do not indicate that media attention has an impact on any measure of suppression expenditures over the days of firefighting that follow.

My results indicate the media's attention to wildfire does not have any bearing on day-to-day suppression decisions. The coefficient estimates on media attention in the second stage of my 2SLS specification indicate a null relationship with daily measures of aerial suppression effort

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[56] Or in the case of suppression costs, it could be that the resources requested by incident managers today are reflected in suppression costs tomorrow.

Table 3.6: Second stage: Impact of media attention on LAT suppression effort allocations.

Contemporaneous	(1) LAT drops	(2) LAT drops	(3) LAT drops	(4) LAT drops
% of internet media	21.257	12.357	-1.547	9.598
	(37.423)	(74.351)	(4.659)	(7.290)
Count of TV networks	-46.816	345.926	-16.458	21.762
	(150.188)	(1464.684)	(38.021)	(31.596)
Next three days	LAT drops	LAT drops	LAT drops	LAT drops
% of internet media	14.681	122.981	-6.416	19.057
	(84.391)	(564.509)	(14.161)	(17.287)
Count of TV networks	1.591	-13.004	-1.413	4.064
	(8.100)	(19.037)	(3.218)	(3.262)
Next seven days	LAT drops	LAT drops	LAT drops	LAT drops
% of internet media	-46.816	345.926	-16.458	21.762
	(150.188)	(1464.684)	(38.021)	(31.596)
Count of TV networks	-5.084	-41.395	-3.626	4.645
	(19.608)	(41.263)	(8.431)	(6.576)
Weather controls	No	Yes	Yes	Yes
Preparedness controls	No	Yes	Yes	Yes
Incident F.E.	No	No	Yes	Yes
Day-of-incident F.E.	No	No	No	Yes
GACC F.E.	No	No	No	Yes
Observations	4,336	4,336	4,321	4,138

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the state level in parentheses.

Each coefficient estimate comes from its own regression.

Table 3.7: Second stage: Impact of media attention on suppression costs.

	(1)	(2)	(3)	(4)
Contemporaneous	Dollars ($1000s)	Dollars ($1000s)	Dollars ($1000s)	Dollars ($1000s)
% of internet media	25715.390	-3295.891	-2258.987	-6408.742
	(50254.544)	(14229.091)	(4090.461)	(6751.091)
Count of TV networks	1786.356**	2793.034	-610.511	-1467.565
	(874.352)	(7133.941)	(1068.031)	(1511.415)
Next three days	Dollars ($1000s)	Dollars ($1000s)	Dollars ($1000s)	Dollars ($1000s)
% of internet media	1777144.725	12387.753	-3819.232	-24529.947
	(3.172e+08)	(14447.493)	(16713.068)	(17008.733)
Count of TV networks	2419.082	25881.075	-838.567	-4552.560
	(3016.117)	(103350.549)	(3531.040)	(3037.865)
Next seven days	Dollars ($1000s)	Dollars ($1000s)	Dollars ($1000s)	Dollars ($1000s)
% of internet media	-7127.530	83043.754**	-21797.738	-49105.649
	(217613.611)	(40711.561)	(36211.856)	(43404.388)
Count of TV networks	358.564	95541.221	-5716.469	-11573.526
	(8918.820)	(212384.462)	(8302.190)	(9855.868)
Weather controls	No	Yes	Yes	Yes
Preparedness controls	No	Yes	Yes	Yes
Incident F.E.	No	No	Yes	Yes
Day-of-incident F.E.	No	No	No	Yes
GACC F.E.	No	No	No	Yes
Observations	2,333	2,333	2,319	2,234

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the state level in parentheses.

Each coefficient estimate comes from its own regression.

and firefighting costs. Swanson, Labrecque, and Hernán 2018 make the case that researchers need to be careful in interpreting null results with instrumental variable regression, especially for time-varying treatments. There are two types of null causal relationships that I can test for - a sharp null and an average null. Media attention would have a sharp null causal effect if it did not affect wildfire management at *any point* in a fire's duration. I can test that by evaluating if $E[Y_t|CE = 1] = E[Y_t|CE = 0]$ for every value of t. I find that the expected value for LAT drops and suppression costs in my sample differs for some t's, leading me to reject the null hypothesis of a sharp causal null effect. This means that I can't rule out that media attention may have an influence on the suppression decisions for *some* wildfires.

There could be an average causal null relationship if media attention doesn't affect suppression outcomes in the aggregate (or on average), even if it affects decisions on some fires (Swanson, Labrecque, and Hernán 2018). I can test this hypothesis by evaluating if $E[Y|CE = 1] = E[Y|CE = 0]$. If the values are statistically different, and I assume monotonicity[57], then I would fail to reject the null hypothesis of an average causal effect. T-tests show that these values aren't statistically different, meaning I fail to reject the null hypothesis of an average causal null impact of media on wildfire suppression. This means that, according to my results, media attention won't have an effect on suppression decisions on the average wildfire.

A comparison of the second-stage coefficients from my 2SLS model and the naive OLS estimates on media attention demonstrates that simultaneity creates an upward bias. In the naive regression, I find that online media attention has a positive and statistically significant relationship with suppression decisions. I did not find a statistically significant relationship when instrumenting for variation in media attention. The results of the Montiel-Pfueger test from my first stage give evidence that my instrument is not introducing as much bias as OLS estimation would. That means the sign on the bias must be positive, signaling the direct pathway of simultaneity, indicated by the relationship between x_{fd} and y_{fd} in Figure 3.1; is stronger than the indirect; indicated by

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[57] This assumption would be violated if the sign on media's treatment effect differed for some individuals (wildfires) in the population (sample).

the relationship between y_{fd} and μ_{fd} in Figure 3.1. Media outlets are more likely to give attention to wildfire as a function of the suppression effort employed than they would be from changes in wildfire behavior from these decisions[58].

3.4.2 Placebo Analysis

A placebo analysis is conducted as an additional test of the robustness of my instrument in the first stage of my model. I randomly assign 10 dates during my sample period (2017 through 2019) as placebo events[59], then evaluate if these falsified instruments would satisfy the "relevance condition". Table 3.8 shows coefficient estimates and standard errors for a regression of media attention on the randomized placebo events. It is apparent from these estimates that the "relevance condition" would not be satisfied using a falsified set of catastrophic events. All effective F-stats derived using falsified events have values less than 2; we cannot reject a null hypothesis that instrumenting with these events won't remove bias.

3.4.3 Denied Resource Requests

My analysis of the impact media attention has on wildfire suppression strategy has, thus far, only considered the potential for it to generate a misallocation of firefighting resources. It's possible that media scrutiny could have benefits to wildfire suppression strategy by increasing the likelihood that incident management teams have their requests fulfilled. I obtain data from the Forest Service on the denied requests (also termed UTFs for "unable to fulfill") for LATs from 2017 to 2019. Table 3.9 contains coefficient estimates from the same OLS model used to generate the results shared in Tables 3.2 and 3.3, where the dependent variable is the number of UTFs for LATs. The results from this naive regression indicate that more television networks covering wildfire in

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[58] If the primary pathway of simultaneity was through the indirect channel, then IV estimates would grow larger than OLS's in this context. Traditional OLS estimates would understate the impact of media attention because it would not capture the tendency of media to scale down coverage as wildfire outcomes evolve to be less severe as a function of a more aggressive suppression strategy.

[59] I define treatment as the week that follows these falsified events, just as I do with the set of catastrophic events I use as instruments.

Table 3.8: First stage: Impact of *placebo* catastrophic events on the online media coverage of wildfire.

	(1)	(2)	(3)	(4)
Media measure #1	% of internet media attention	% of internet media attention	% of internet media attention	% of internet media attention
Catastrophic event	-0.001 (0.006)	-0.004 (0.008)	-0.006 (0.009)	-0.004 (0.009)
Media measure #2	Count of TV networks	Count of TV networks	Count of TV networks	Count of TV networks
Catastrophic event	-0.041 (0.047)	-0.046 (0.059)	-0.037 (0.067)	-0.025 (0.062)
Weather controls	No	Yes	Yes	Yes
Preparedness controls	No	Yes	Yes	Yes
Incident F.E.	No	No	Yes	Yes
Day-of-incident F.E.	No	No	No	Yes
GACC F.E.	No	No	No	Yes
Observations	4,336	4,336	4,321	4,138

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the state level in parentheses.

Each coefficient estimate comes from its own regression.

a state would lead to more denied requests for LATs. I find a similar pattern with internet media attention, except for the model that includes day-of-incident fixed effects (Column 4).

Table 3.10 contains coefficient estimates for a model that instruments for the impact of media attention using my set of catastrophic events, similar to Tables 3.7 and 3.6. The top panel contains results for the impact of internet and television media on contemporaneous denied requests for LATs; the bottom panel has the equivalent results for denied requests on the next day. We do not observe a statistically significant relationship between media attention and denied LAT requests aside from the contemporaneous models that include all controls and incident and regional fixed effects in Column 3; true for both internet and television media. According to these coefficient estimates, a one percent increase in the share of total internet media dedicated to wildfire in a state would correspond to 2.6 fewer denied requests for LATs to wildfires in that state. An additional television network with a national story about wildfire would correspond to 0.58 fewer denied requests for LATs.

Table 3.9: OLS regression of media attention on denied LAT requests.

Contemporaneous	(1) LAT UTFs	(2) LAT UTFs	(3) LAT UTFs	(4) LAT UTFs
% of internet media	0.492***	0.452***	0.216**	0.086
	(0.062)	(0.098)	(0.072)	(0.060)
Count of TV networks	0.116***	0.103***	0.050***	0.027**
	(0.009)	(0.009)	(0.014)	(0.011)
Weather controls	No	Yes	Yes	Yes
Preparedness controls	No	Yes	Yes	Yes
Incident F.E.	No	No	Yes	Yes
Day-of-incident F.E.	No	No	No	Yes
GACC F.E.	No	No	No	Yes
Observations	4,336	4,336	4,321	4,138

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the state level in parentheses.

Each coefficient estimate comes from its own regression.

Table 3.10: Second stage: Impact of media attention on denied LAT requests.

Contemporaneous	(1) LAT UTFs	(2) LAT UTFs	(3) LAT UTFs	(4) LAT UTFs
% of internet media	2.707	-1.343	-2.609**	-1.157
	(3.638)	(9.575)	(1.130)	(1.122)
Count of TV networks	0.293	0.143	-0.575*	-0.247
	(0.256)	(0.665)	(0.267)	(0.264)
One-day lag	LAT UTFs	LAT UTFs	LAT UTFs	LAT UTFs
% of internet media	1.778	-3.067	-1.505	-0.401
	(3.097)	(13.769)	(1.070)	(1.177)
Count of TV networks	0.192	0.328	-0.332	-0.086
	(0.249)	(0.615)	(0.223)	(0.256)
Weather controls	No	Yes	Yes	Yes
Preparedness controls	No	Yes	Yes	Yes
Incident F.E.	No	No	Yes	Yes
Day-of-incident F.E.	No	No	No	Yes
GACC F.E.	No	No	No	Yes
Observations	4,336	4,336	4,321	4,138

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors clustered at the state level in parentheses.

Each coefficient estimate comes from its own regression.

3.5 Discussion

The results from the first stage of my 2SLS model show that catastrophic events could be a useful instrument for any researcher evaluating the impact of media on disaster management. If researchers are interested in determining whether media attention influences the resources that are allocated in the aftermath of a hurricane, there might be concerns that those allocations are also affecting the media's coverage decisions. If the exogeneity condition and exclusion restriction hold between events such as mass shootings and wildfire management, they will likely hold also for the management of hurricanes and flooding. The statistical significance and effective F-statistics from my first stage show that the "relevance condition" holds. The null effect found using a set of placebo dates provides even more evidence that catastrophic events truly crowd out media attention to wildfires. This would be easily testable for other types of natural disasters, given data on resource allocations in their context. This approach provides an encouraging framework for future studies that aim to disentangle the complex interaction between media coverage and disaster management.

There are several reasons to believe that media attention will not have an influence on suppression decisions, despite having an effect in other contexts (Jetter 2014; Koning, Mertens, and Roosenboom 2010; Donovan, Prestemon, and K. Gebert 2011). Wildfire resource decisions are mainly a function of operational considerations such as resource availability, wildfire conditions, weather, or threatened structures (Bayham and Yoder 2020; Belval, Wei, et al. 2017; Bayham, Belval, et al. 2020). Resource allocations are made based on real-time assessments by on-the-ground incident commanders prioritizing immediate tactical needs. Input from fire behavior analysts, meteorologists, or other experts is heavily relied upon when making decisions; my results suggest that decisions are generally not driven by narratives in the media.

The decentralized nature of wildfire resource allocation and suppression also supports a statistically null relationship between media attention and wildfire. Wildfire suppression is typically coordinated among a network of different land management agencies or other stakeholders, each with their own set of institutional constraints (Kelly, Susan Charnley, and Pixley 2019). In this type of system, the effect of media attention could be diluted across the different levels of decision-making and resource allocation. It's also possible that incident managers aren't influenced by the media because they feel insulated from its pressure by the variety of different institutional guidelines prioritizing safety over scrutiny.

My results indicate a null relationship between media attention and day-to-day suppression decisions, but it's possible that the media's focus could serve as a mechanism for incident managers to secure critical resources. Heightened media scrutiny might help managers receive more firefighting resources by drawing attention to their suppression efforts, increasing the likelihood that a resource request is granted. This could be especially useful when resource constraints are binding if there is more pressure on regional coordinators to allocate resources like LATs to incidents in need of additional support. My analysis of denied LAT requests doesn't provide strong evidence that the media helps incident managers receive aerial resources they feel are needed. The lack of an observable effect suggests that media may aid in generating public awareness, but that doesn't translate into tangible benefits to incident management. This result highlights another limitation in the potential for the media to directly influence wildfire outcomes, particularly in obtaining specialized resources at important points in a suppression campaign.

I do not find that the attention of the media to wildfires has an effect on day-to-day suppression decisions, but there are other ways the media could influence incident management. Increased media scrutiny may influence suppression decisions on future wildfires, even if it doesn't affect ones currently burning. For example, an incident manager could approach the "initial attack" phase of their next fire differently due to the scrutiny received on the current wildfire. Media pressure may not be felt the strongest at the wildfire level, but rather at the agency or federal level. If that were the case, the media's influence on wildfire outcomes may be more significant in shaping policy decisions than it would be in altering day-to-day wildfire management. Sustained media coverage could also result in changes to public opinion, prompting land managers to adjust their long-term strategies and resource allocations. These broader effects highlight the other channels that media could influence wildfire management through.

This work has significant policy relevance as governing bodies decide how much access they are willing to provide to media outlets. There exists policy variation across states on who is restricted from accessing wildfire (Har and Fonseca 2020), with Oregon recently making policy changes over the media's access. If media attention is indeed causing a misallocation, we will want to consider building systems that reduce the incentive (or increase the disincentive) of aggressive suppression strategy in situations where it is not necessary. The media provides an important public good, keeping citizens aware of recent developments on a wildfire, allowing them to update their priors regarding their personal risk exposure, and drawing attention to the environmental issues contributing to increasing wildfire intensity. If we incorrectly assume that media attention leads to a misallocation of resources, that might cause some state/local governments to consider taking more conservative approaches to wildfire reporting, reducing the quantity and/or quality of information received by citizens. My research does not support such a restriction, as the reduction in information would not be followed by an improvement in resource allocations.

3.6 Conclusion

The purpose of this study is to test whether the media's attention to wildfire has any effect on suppression outcomes. I use two-staged least squares (2SLS) estimation out of concerns of simultaneity, instrumenting with occurrences of catastrophic events like a mass shooting. In the first stage, I show that catastrophic events do crowd out the amount of media attention going to wildfire. In the second stage, I use the instrumented variation in media attention to find that it has no bearing on suppression effort allocations or firefighting costs. This is true both contemporaneously and for suppression outcomes measured over three and seven days.

My findings support further investigation of the broader impact of media attention on wildfire management. Future research should explore how media attention influences post-wildfire recovery efforts, long-term resource planning, and the allocation of risk mitigation projects like fuels treatment. Additionally, the role of social media, with its ability to spread information rapidly, remains an important area for future inquiry. Reseach on these dimensions would allow us to better understand the complex interactions between media coverage, public perception, and disaster management.

There are several important contributions to the literature on wildfire resource allocation, media attention, and natural resource management. First, I build upon Donovan, Prestemon, and K. Gebert 2011's work analyzing the relationship between media attention and suppression costs. I improve on their work by considering sources of media attention that are more relevant to the current media landscape: the internet and television. I also focus on the impact of these sources of attention on the allocation of suppression effort, not just their costs. I also contribute to the larger literature on natural resource management by developing a framework to evaluate whether media attention has an influence on resource decisions for any type of natural disaster, as long as standard IV assumptions hold in its context. This research builds on the work Donovan, Prestemon, and K. Gebert 2011 even further by showing the relationship between daily measures of suppression expenditures and media attention, rather than incident-wide.

This research contributes to the literature on the impacts of media attention on two distinct margins. First, my findings corroborate the work of others that shows that media has minimal impact on outcomes in certain settings (Philippas et al. 2019). Second, given my daily measures of media attention and suppression decisions, I also contribute to the literature on the timing of the media's impact (Larsen and Thorsrud 2022) by finding no contemporaneous effect.

Chapter 4

Is that $30,000 drop effective?

Abstract:

Climate change has intensified wildfires in North America, driving their suppression to be a multi-billion dollar expenditure annually. We need to understand the effectiveness of wildfire suppression strategies to calculate their economic benefits. The objective of this study is to estimate the effectiveness of aerial firefighting in suppressing wildfire growth. We use high-resolution spatiotemporal data on the location and times of large airtanker (LAT) retardant drops, along with satellite data on daily wildfire growth. We estimate the effectiveness of large airtankers at suppressing wildfire in both a spatial difference-in-differences model and a regression discontinuity. We find that large air tankers are effective at limiting the spread of wildfire, diminishing the intensity of its burn, and delaying the spread of the wildfire. We estimate that the federal government spent around $89,000 per year on LAT suppression per home protected from wildfire.

4.1 Introduction

Wildfires impose a significant economic burden on society, not only due to their destructive nature but also because they are costly to control. In the United States, the increased prevalence of simultaneous large wildfires (McGinnis et al. 2023) has intensified competition for resources used to suppress wildfire growth, like hand crews, fire engines, and helicopters. The federal government today operates a fleet of firefighting aircraft, including large air tankers (LATs), which are in limited supply nationwide (Andersson 2023). We have robust knowledge of the financial cost of aerial wildfire suppression, but our understanding of the economic benefit or substitutability with other suppression resources is limited. We need to determine the conditions that maximize LAT effectiveness if we are to build a model of optimal aerial suppression, therefore minimizing the total economic costs of wildfire.

The objective of this study is to determine the cost-effectiveness of LATs in achieving wildfire management objectives. We do this by measuring the baseline suppression effectiveness of LATs and then evaluate the conditions that lead them to be the most effective at limiting wildfire growth. We build a unique dataset that leverages information on the times and locations of fire retardant drops from LATS and wildfire outcomes measured down to the 30-meter level. We employ a spatial difference-in-differences estimator to causally identify the effect of these retardant drops on the wildfire's extent, intensity, and rate of spread. We then use a regression discontinuity to assess the robustness of those estimates. We find that LATs are effective at reducing the extent of wildfire, diminishing the intensity of burn, and slowing its spread.

This study contributes to the literature on wildfire suppression strategy on four distinct margins. First, it is the first study to *causally* identify the effectiveness of a wildfire suppression resource's ability to contain and control active wildfire. Two, this research highlights the conditions most favorable to a "successful" retardant drop that can later inform a model of the optimal LAT resource allocation. Third, we propose a metric to evaluate the cost-effectiveness of LAT retardant drops. Finally, this research provides an example of a unique estimation strategy to causally identify the effectiveness of interventions to any spatially evolving phenomenon, such as invasive species spread or flooding.

We also analyze factors driving heterogeneity in LAT suppression effectiveness, finding that they are most effective when dropping on shrub-type vegetation or steep slopes. LATs are significantly more effective at delaying the spread of fire when used in concert with other forms of suppression (ex: hand-dug line) but no more or less effective on other margins. We propose a metric to parameterize the cost-effectiveness of LAT drops; we estimate that the federal government spent around $89,000 per year on LAT suppression per home protected from wildfire.

The rest of the paper will be organized in the following manner. In Section 2, we frame the economic implications of wildfire suppression strategies and provide a brief background on large airtankers and how they're used to control wildfires. In Section 3, we describe the two identification strategies employed to determine the suppression effectiveness of LATs and the econometric specifications used. We then discuss the data sources and subsequent processes used to create our dataset for this analysis. Section 4 contains results from our baseline difference-in-differences estimation, as well as those for models identifying heterogeneity in effectiveness. we discuss how "cost-effectiveness" is calculated for our set of drops in Section 5 and share the results of that calculation. In Section 6, we discuss the implications of our results. Finally, in Section 7, we provide some concluding remarks and explain how we expect this research to progress in the short, medium, and long run.

4.2 Background

Wildfire is a natural process that has ecological and economic benefits, but it also poses significant adverse consequences for society. It can directly threaten people's lives and homes (Bayham and Yoder 2020; Baylis and Boomhower 2023), worsen health outcomes through smoke exposure (Burke, Heft-Neal, et al. 2022; D'Evelyn et al. 2022), disrupt economic activity (D. Wang et al. 2020), and impact the value provided by ecosystem services in the areas affected (Pereira et al. 2021; Robinne et al. 2020). Wildfire economic damages have surged in recent years, driven by more people living in the wildland-urban interface (Radeloff, Helmers, Kramer, Mockrin, Alexandre, Bar-Massada, Butsic, Hawbaker, Martinuzzi, Syphard, and Stewart 2018) and the increasing severity of wildfires (Weber and Yadav 2020). As a result, smoke-related damages have risen for those exposed. Reducing these growing economic impacts is now a top priority for land managers and policymakers worldwide.

Controlling wildfire is inherently an economic problem, as incident managers minimize the sum of wildfire damages and suppression costs while facing strict resource constraints. Incident managers or teams develop strategies and deploy firefighters to reduce the damages from wildfire on people, property, and other valued assets. Understanding the decision-making process of incident managers (also referred to as "IC"s) is crucial for evaluating the effectiveness and efficiency of wildfire suppression efforts. Theoretically, ICs make resource decisions based on assumptions about their marginal effectiveness (Bayham and Yoder 2020). Despite this fact, the federal government does not employ a “one size fits all” method for wildfire suppression. Hand, Katuwal, et al. 2017 shows that ICs vary in the suppression strategies they employ [60].

Various factors aside from wildfire behavior play a crucial role in shaping the suppression strategies employed by ICs. The presence of threatened values at risk, such as homes, businesses, community establishments, or watersheds, are important determinants of wildfire suppression strategy. Bayham and Yoder 2020 find that both the number of threatened homes and their value are important factors in the amount (and type) of suppression resources provided to an incident management team. Weather is another important determinant of resource orders (Bayham, Belval, et al. 2020), especially for aviation as extreme winds can make aerial suppression difficult. Features of the land threatened by wildfire will also influence suppression strategy (Daniels et al. 2024) including the terrain or vegetative fuel types/concentration. For example, ICs may prefer to use aviation in places that are difficult to reach on the ground. The scarcity of available suppression resources is another important determinant of the strategy employed by an IC (Belval, Stonesifer, and Calkin 2020a); this is particularly true for the resources used for aerial firefighting (Stonesifer, Calkin, Thompson, and Belval 2021).

Large airtankers (LATs) have been used to fight fire in the United States dating back to 1955 (NWCG 2023). These aircraft are typically military or commercial aircraft retrofitted to disperse large amounts of fire retardant to a general area during a wildfire (see Figure 4.1). The fire retardant that LATs drop helps to contain wildfire by using a mixture of fertilizer and water that raises the threshold temperature needed to ignite vegetative fuels (Stonesifer, Calkin, Thompson, and Stockmann 2016). In practice, LATs drop retardant beyond the fire’s current perimeter in anticipation of its spread[61], with the intention of pre-treating potential fuels (Stonesifer, Calkin, Thompson, and Stockmann 2016). The suppression objectives that incident managers most often task LATs with

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[60] In this paper, they use “IC fixed effects” to find that these managers even have consistent preferences over strategy across different wildfires. This suggests that, theoretically, certain ICs may prefer to use aircraft for the initial attack of a wildfire while others might prefer to use on-the-ground suppression resources.

[61] This is in opposition to the other two main forms of aerial suppression: helicopters and scoopers. Those resources typically dump water directly onto the wildfire.

Figure 4.1: Large airtanker (LAT) delivering a load of fire retardant ahead of an advancing flame front. Photo by Ian James, courtesy of *Wildfire Today*.

are halting the spread of wildfire or delaying the spread to provide point protection to values at risk like homes, structures, or watersheds (U.S. Forest Service 2020).

The allocation of LATs hinges not only on the magnitude of potential damages but also on the probability that their deployment will effectively reduce these damages. There is a high degree of uncertainty concerning how a wildfire might spatially evolve over its duration, similar to other climate events like hurricanes. It is impossible for land managers, ICs, or pilots to know precisely what direction a fire will spread, at what speed or intensity, or how much longer it will last. The uncertainty over expected damages from a wildfire means that we should expect suppression strategy to be a function of both the total potential damages and the probability of a resource's output being successful in damage reduction (Wibbenmeyer, Hand, et al. 2013).

Technological advancements in GIS mapping, including drone and satellite imagery, can aid in measuring the effectiveness of suppression techniques (Baijnath-Rodino et al. 2023). Geospatial tools such as drone and satellite imagery offer the potential to precisely evaluate effectiveness by tracking fire behavior before and after interventions. Once quantified, information on aerial suppression effectiveness will be an essential input to any decision support framework geared toward aviation (Stonesifer, Calkin, Thompson, and Stockmann 2016).

The Forest Service (USFS) has recently invested financial and human capital into research on how it can optimize its aerial firefighting fleet. The Aerial Firefighting Use and Effectiveness Study (U.S. Forest Service 2020) (AFUE) was a wide-ranging analysis of our aerial firefighting infrastructure. Their study focused on the capacity of different types of firefighting aviation to produce suppression output, not change wildfire outcomes. However, a comprehensive evaluation of suppression tactics must account for their direct influence on fire dynamics, such as slowing its growth and reducing flame intensity (Finney et al. 2011). Our research improves upon the AFUE study by measuring how effective a particular type of aircraft is at altering wildfire outcomes.

Several studies have analyzed the effectiveness of different suppression resources and strategies. Gannon, Thompson, et al. 2020 develop metrics that land managers or ICs could use to better understand not only how successful a containment line was at holding against the fire, but also how effective it was in engaging with the wildfire in the first place. Holmes and Calkin 2013 estimate parameters for an economic production function for containment line; their results indicate there are increasing returns to scale in wildfire suppression. Katuwal, Calkin, and Hand 2016b find that physical capital (dozers/fire trucks) are more effective at producing containment than human capital (firefighters). These studies define effectiveness using spatial metrics that describe the likelihood of a suppression resource physically engaging with the wildfire, not its ability to reduce the spread of the fire or its flame intensity. Other recent studies have sought to quantify the costs and benefits of other suppression strategies (Bayham and Yoder 2020; Plucinski 2019; Pennick McIver, Cook, and Becker 2021). Still, similar to the Forest Service's report on aviation, these studies did not measure benefits through the physical capacity to slow wildfire's spread.

4.3 Methods

In this section, we outline the methodological approach used to estimate the effectiveness of large airtanker (LAT) retardant drops in altering wildfire growth. The analysis is grounded in two primary identification strategies: Spatial Difference-in-Differences (DiD) and Regression Discontinuity Design (RDD). These methods are selected to address the non-random allocation of aerial firefighting effort, ensuring that both observable and unobservable biases are adequately considered.

The Spatial DiD approach enables us to estimate the overall treatment effect of LAT drops by comparing the outcomes in treated and untreated land. This method is particularly suited to capturing the broader effects of suppression efforts, accounting for the complex dynamics of wildfire spread. We complement the DiD analysis with an RDD to ensure the robustness of our findings. The RDD provides a sharper estimate of the causal impact of LAT drops by focusing on land immediately adjacent to the drop line.

Section 3.1 details the identification strategies, including how treatment and control groups are defined and the econometric specifications used. Section 3.2 describes the data sources, the processing steps undertaken to create the dataset, and the variables used in the analysis. Together, these methods form a comprehensive framework to evaluate the effectiveness of LAT retardant drops, highlighting conditions that maximize aerial firefighting success.

4.3.1 Identification Strategy

Analyzing the effectiveness of wildfire suppression resources is challenging because suppression efforts are not randomly assigned. ICs make strategic decisions on placement of resources like large airtankers (LATs) based on expectations about wildfire growth. Suppression efforts are usually directed at locations where management expects the greatest marginal benefit from the intervention.

As a result, we cannot simply estimate the effectiveness of aerial suppression by comparing protected land to unprotected land. The location of suppression effort will be assigned as a function of expectations about wildfire behavior. The areas that received suppression are likely to differ systematically from those that did not, not just because of observable factors like terrain and vegetation but also due to unobservable factors such as strategic priorities. This selection bias can obscure the true effects of suppression by conflating them with the underlying characteristics that drove the firefighting decisions.

To address this selection problem, we can take advantage of the inherent randomness in the exact placement of LAT drops. The precise location of each retardant release, down to the meter, depends on factors such as pilot skill, wind conditions at the moment of the drop, the topography of the target area, and the physical condition of the aircraft. These variables introduce a degree of randomness, enabling a more credible estimation of the suppression effect.

While aerial suppression is not allocated to a general location at random, we can estimate the effectiveness of LAT suppression by comparing land that was treated to nearby land that wasn't. Pilots releasing a retardant drop may only have general guidance on the intended location; for example, they could be told to drop "on the eastern flame front of the wildfire's northern perimeter". However, the location of that retardant release down to the meter will also be a function of factors like pilot ability, wind conditions at the exact time of drop, topography of target land, or physical condition of the aircraft. Therefore, the precise location of LAT drops down to the meter has an element of randomness.

Figure 4.2 gives a visual depiction of this spatial nuance; the first image on the left (panel A) contains a map of the Terek fire in Wyoming in 2018, while the second image on the right depicts a single retardant drop on the southern edge of the fire's perimeter. Figure 4.2 shows that suppression effort is mostly concentrated at the southern part of this fire's perimeter, likely due to some integral combination of factors affecting the suppression strategy, such as the presence of a highway to the south[62].

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[62] Incident notes state that there was heavy timber south of the fire's perimeter, so there were concerns that if the fire spread in that direction, it had the potential to increase significantly in severity.

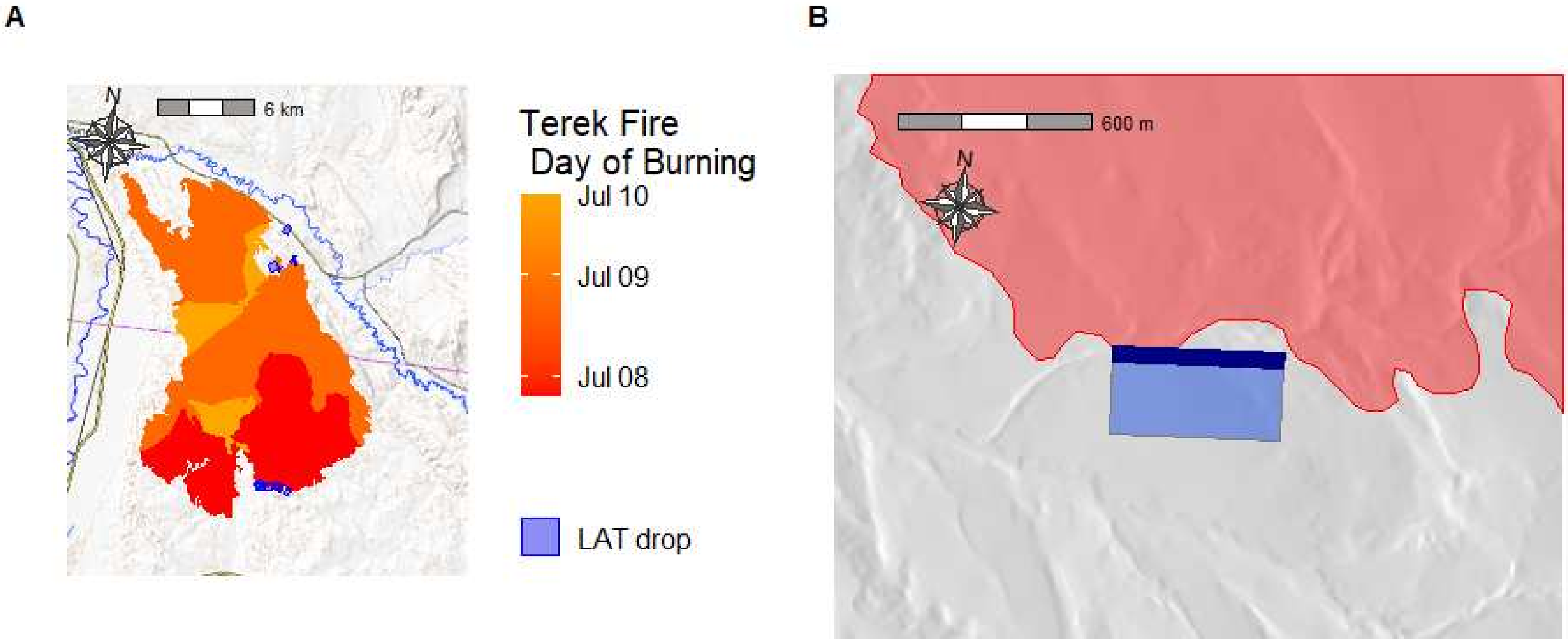

Figure 4.2: Map of aviation use on the 2018 Terek fire (WY). Aviation use on the entire fire in Panel A. A single drop on the southern perimeter of the fire in Panel B.

The adjacent plot (panel B) of Figure 4.2 focuses on the thick navy blue line just south of the fire's perimeter, representing a single retardant drop from a LAT. The land on the opposite side of the retardant from the fire, shaded with an opaque navy color, is the most logical land to have been targeted for protection by the LAT[63]. This area will be defined as "treated" in our analysis.

The random nature of the exact locations of retardant drops, combined with the strategic assignment of general suppression locations, forms the basis of the identification strategies employed in this study. Specifically, we take advantage of this randomness through a spatial difference-in-differences (DiD) estimation. We then use a regression discontinuity design (RDD) to assess the robustness of our DiD results. These approaches allow for a more accurate estimation of the causal effect of LAT suppression on wildfire outcomes.

Difference in Differences

In this analysis, our goal is to understand the effectiveness of LAT retardant drops in altering outcomes on an active wildfire. The simplest way to do this would be to compare wildfire outcomes on land protected by a drop to land that was left unprotected. Comparing wildfire outcomes would be simplest if we could find perfectly identical areas of land or randomly assigned retardant drops. However, perfectly identical landscapes don't exist, and randomly using aerial suppression without considering threats to lives and property would violate ethical land management practices. This provides a setting for difference-in-differences estimation using a two-period panel setup, similar to the one outlined in Nguyen 2012, with treatment units matched to control units[64].

It wouldn't be appropriate to compare the land protected by a drop with any random, equally-sized area threatened by the wildfire that didn't receive aerial suppression. The land that was selected for aerial suppression treatment was chosen due to some combination of factors relevant

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[63] It's plausible that land further removed from the retardant was also considered when developing a suppression strategy with a LAT, but it is difficult to know what land that would have been in a post-hoc analysis.

[64] The matching process in Nguyen 2012 is quite different from ours, but our panel setup for difference-in-differences is very similar.

to the incident management's suppression strategy. Large stretches of land that aren't selected likely diverge on one (or several) of these factors, making them implausible counterfactuals.

However, we can match land treated by a drop to untreated land if they were broken down into cells that are much finer on a spatial scale[65], taking advantage of the randomness described earlier in the precise coordinates of aerial suppression allocations[66]. LAT pilots don't select drop locations at random, but there is some variation in where the retardant drop begins and ends. This means that the cells of land that are "treated" by aerial suppression effort toward the beginning of a drop have plausible counterfactuals: the adjacent land that isn't protected from the wildfire by retardant.

Figure 4.3 provides a visual depiction of our identification strategy. We define our treatment variable, aerial suppression, as T_i. The cells in the area labeled A & B represent our treatment units and would all receive a value of $T_i = 1$. The area labeled C & D contains the land that we use to pull cells from for matching with our treatment units, as this land does not receive aerial suppression ($T_i = 0$).

Pre-treatment and post-treatment units are defined based on the geographic relationship of the drop to the approaching wildfire. If a cell is in front of the retardant line relative to the fire (in between the drop and the fire), then it is defined as a pre-treatment unit ($P_i = 0$), regardless of whether it is a treatment or control cell. If a cell is behind the suppression line relative to the approaching fire, then it is considered a post-treatment unit ($P_i = 1$). Figure 4.3 also shows this spatial pattern; areas A & C to the north of the line of retardant represent the pre-treatment area for this particular drop, while areas B & D to the south of the drop represent our post-treatment.

Once I have established plausible treatment-control groups, we are able to set up the differences-in-differences (DiD) econometric model:

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[65] This could work in theory with any cell substantively smaller in size than a LAT drop.

[66] This identification strategy may work for other forms of wildfire containment strategy, but is most defensible with aviation as it is the only suppression resource that can instantaneously build containment line. Other forms of containment take longer with more deliberate effort, so there is not as much randomness in their precise locations.

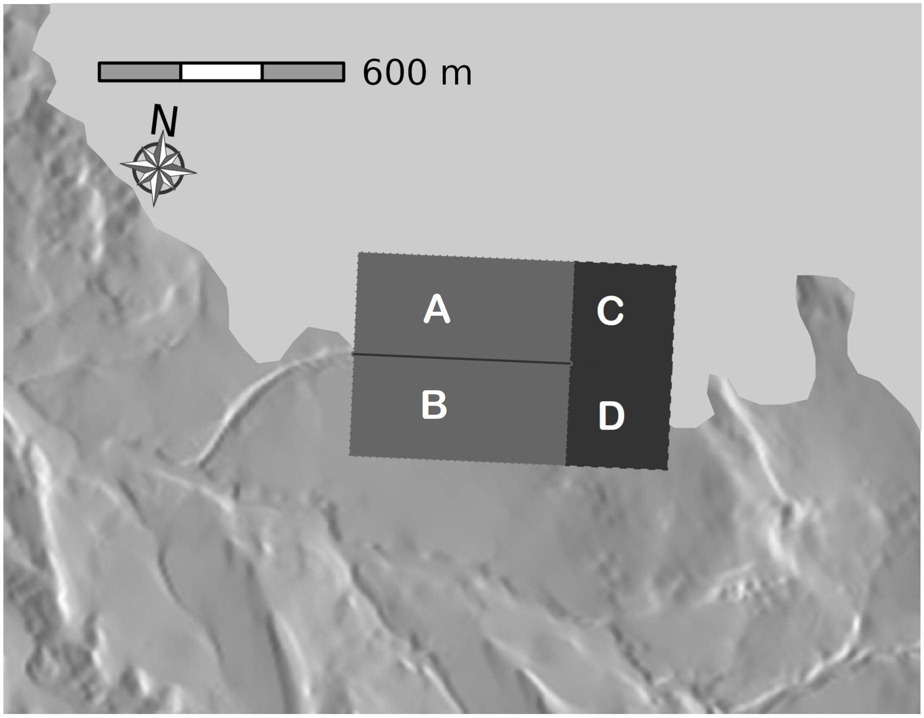

Figure 4.3: Areas that define treatment and control units

$$Y_i = \theta P_i + \gamma T_i + \rho(P_i * T_i) + \beta X_i + \mu_i \tag{4.1}$$

Y_i represents the wildfire outcome of interest for land i. We estimate models using extensive and intensive margin measures of wildfire impacts, as well as the time until the drop-treated land burns. T_i is an indicator for a treatment cell. It will be equal to one if the land is anywhere within a drop's buffer. P_i is an indicator for a cell being behind a drop relative to the wildfire, regardless of being a treated or control unit. ρ is the coefficient on the difference-in-differences variable; this is the parameter for the effectiveness of a retardant drop. X_i is a vector of factors we control for that confound the relationship between aerial suppression effort and wildfire spread. This vector contains information on weather at the time of drop (wind, temperature, PDSI, precipitation, and relative humidity), wildfire hazard potential, burn probability, and vegetation type/concentrations. μ_i represents the error term in this model that captures any unexplained variation in the wildfire outcome of interest on land i.

One potential concern in this analysis is that our control cells could be more likely to burn once a drop is placed nearby because fire is pushed in its general direction. We believe that, if anything, this spatial nuance would overstate the effectiveness of LATs, rather than make them appear to be ineffective. However, to account for this potential bias, we employ a second identification strategy: a spatial regression discontinuity.

Regression Discontinuity Design

We use a spatial regression discontinuity (RDD) to assess the robustness of our primary specification. Our difference-in-differences estimation strategy allowed us to compare the land protected by a drop with the land lateral to it (relative to the drop/fire). With an RDD, we will be comparing the land in front of a retardant line, not protected from wildfire, to the land behind it. We exploit the fact that there is a sharp suppression treatment effect for all land behind the location of the LAT drop. The main assumption of this framework is that all variables that affect wildfire intensity vary continuously across our buffered drops, except for the suppression treatment.

We first assess the plausibility of that assumption, plotting different wildfire-relevant factors over space relative to the retardant line. We find no visual discontinuities, allowing us to pursue estimating the effectiveness of LATs using the following econometric model:

$$Y_i = \rho T_i + \alpha D_i + \beta X_i + \mu_i \tag{4.2}$$

This specification is similar to the difference-in-differences estimator; Y_i, T_i, X_i, and μ_i all represent the same factors in the specification. We include the term αD_i in this specification, where D_i is the running variable, the distance of a cell to the LAT drop. We estimate models using bandwidths of 250 and 150 meters to the drop. Extensive and intensive margin impacts are both modeled using this setup.

There are distinct advantages to each of our estimation strategies, and we believe that they contribute to different margins of our understanding of LAT suppression effectiveness. The RDD approach is well-suited for determining how effective LATs are at halting a fire's spread or diminishing the intensity of its burn. It will give the best sense for a sharp treatment effect (Wuepper and Finger 2023).

However, unlike many medical or policy interventions, it is not straightforward what land units would considered "treated" when it comes to suppression effort allocations. We believe the spatial difference-in-differences framework that we demonstrate in this paper will give a better sense of the treatment effect of a LAT drop in situations when it is unclear what land should be considered treated. The spatial difference-in-differences method accounts for the fact that fire could approach a cell behind the drop from a different angle. This is important, as wildfire does not grow strictly forward, in linear paths, or in any expected way. At times, it can move laterally following a shift in the wind or as it enters new terrain like a box canyon. The RDD treatment estimate gives a strong sense of the likelihood of the LAT drop stopping the fire's spread into specific units of land; the spatial DiD provides a sense of the overall treatment effect of retardant.

An advantage of the spatial difference-in-differences is its ability to detect treatment effects beyond the spatial intervention of interest. For example, a retardant drop that is burned over by the wildfire could still have an extensive margin effect by sharply reducing flame intensity first, allowing the fire to slowly die out as it grows another 100 meters. A spatial RDD would not detect such a non-sharp treatment effect.

There is a distinct assumption required for each of our identification strategies. Stable unit treatment value assumption (SUTVA) violations are a concern when determining the effectiveness of any treatment (Sinclair, McConnell, and Green 2012), particularly in DiD estimation. One potential concern with using the spatial difference-in-differences approach in this context is that LAT drops could push wildfire into the counterfactual area[67], biasing any estimation of LAT suppression effectiveness. An integral assumption with spatial RDD is that nothing changes at the cutoff variable other than the assignment of treatment (Hahn, Todd, and Van der Klaauw 2001). That as-

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[67] There would also be SUTVA violations if ICs were more likely to allocate suppression effort into the counterfactual areas, next to the retardant drop.

sumption would be violated if LATs spatially allocated retardant as a function of some observable or unobservable factor.

We address potential violations of SUTVA, which could bias our results depending on the source of interference, to show the robustness of our DiD findings. The direction of the bias created by a SUTVA violation will be contingent on the source. The increased propensity of wildfire to burn in the control area would bias the effectiveness upward; additional allocations of suppression effort would bias it downward. First, to address the potential of wildfire to get pushed into the control area, we trim the land that we define as our treatment and control areas to account for this spatial spillover. Second, we remove control cells that are buffered by a different retardant drop and include controls for other types of suppression effort. This will account for any increased likelihood of the control area receiving resource allocations.

Third, we produce coefficient estimates using a subset of drops that were orthogonal to the prevailing wind direction on the day the fire approached the retardant line. These results are displayed in C1 of the Appendix. We find coefficient estimates that are larger in magnitude on the extensive and intensive margins with this subset (Tables C3 & C4 in the Appendix). This finding minimizes concern that fire is systematically pushed into our counterfactual space, biasing our estimates. Finally, LATs are often used as a "resource of last resort" (Stonesifer, Calkin, Thompson, and Stockmann 2016). ICs will be unlikely to allocate additional on-the-ground resources to these areas due to extremely hazardous conditions, minimizing this potential pathway for bias to affect our estimated parameter.

The assumption that nothing is changing at the cutoff, an integral assumption for RDD, is stronger than assuming SUTVA in the context of aerial wildfire suppression. There is evidence from discussions with wildfire incident managers that the starting/ending location of a LAT drop is more plausibly random than the general location of a drop. Even though LAT drops might be random in the fore/aft direction down to the meter level, pilots usually have some strip of land in mind when choosing a drop location. We test whether this is a safe assumption with our data (see Figures 4.9 and 4.10 in the Results section) show that there aren't any observable factors changing at the cutoff, but IC or pilot beliefs about suppression effectiveness could be changing sharply at the location of the retardant line. If that's the case, parameter estimates from the spatial RDD would overstate the effectiveness of LATs.

Taken together, this analysis is best served using the spatial DiD as the primary specification and then evaluating the robustness using the RDD. The spatial DiD relies on weaker assumptions in this context and will give a more conservative estimate. The spatial RDD is well-equipped to evaluate the robustness of the findings from the DiD because it does not rely on a similar counterfactual area, absolving SUTVA concerns. In the next subsection, we describe the unique dataset we put together to carry out our identification strategy.

4.3.2 Data

We construct a unique two-period panel dataset[68] to analyze the effectiveness of aerial suppression. Data is provided by the Forest Service on the exact times and locations of aerial suppression effort allocations. Information on the daily progression of wildfires is extrapolated using the Parks 2014 method and satellite data made available from NASA. Geographic information on the wildfire hazard conditions from publicly available resources is included in our data. Spatially fine information on weather is acquired from Gridmet (Abatzoglou 2013) and also included in the data.

Aerial suppression effort data comes from Additional Telemetry Units (ATUs) mounted onto LATs. ATUs record the exact geographic coordinates and time stamps of the doors opening (and closing) on the hull of a LAT to deliver a load of fire retardant. We use these data for 224 wildfires[69] from 2017 to 2019, a sample of over 3,000 spatial lines. These data come from LATs, capable of delivering 2000 to 4000 gallons of fire retardant, and very large air tankers (VLATs), capable of delivering over 8000 gallons of fire retardant (USFS 2023).

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[68] The periods are defined by space, not time. The first period is the land in front of the large airtanker (LAT) drop, the second period is the land behind the drop.

[69] The data contains drops from fires in the states of Washington, Oregon, Arizona, New Mexico, Colorado, Wyoming, Utah, Montana, and Nevada.

Figure 4.4 shows the distribution of LAT drop distances. LAT drops don't take to a uniform length, indicating there is random variation we can use to define our treatment and control areas. Each drop is extended by a factor relative to its length in the direction of the drop's release point using GIS processing in R with the "sf" package. Those new lines are then buffered by the same distance as the drop to create the areas from which we extract control units.

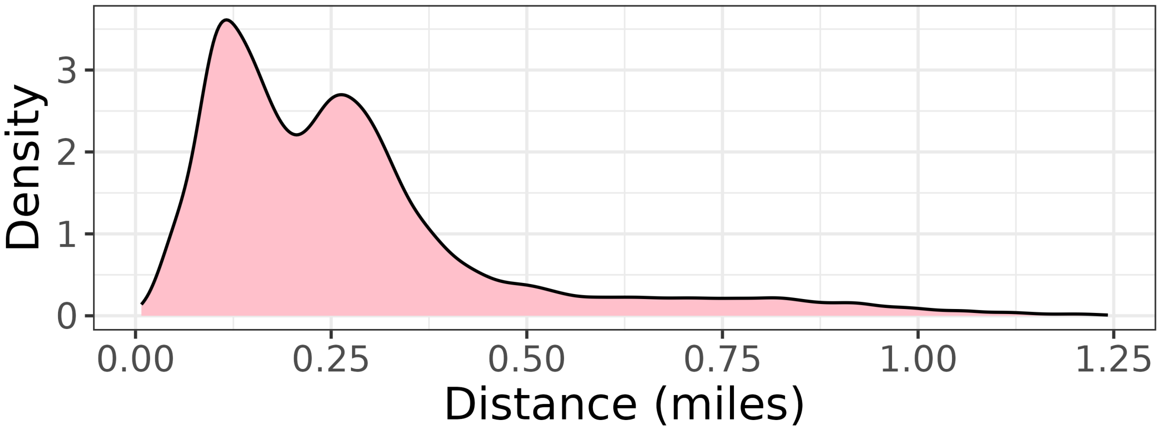

Figure 4.4: Density of drop distances

Wildfire perimeters are reliably reported at the end of an incident. Our analysis relies on spatiotemporal variation. We estimate daily wildfire growth using the method described in Parks 2014. Parks's method leverages spatial data on final wildfire perimeters and satellite data from NASA on fire intensity (MODIS and VIIRS) to create daily perimeters of a wildfire. The end result is a spatial layer of a wildfire resolved at 30-meter resolution with a value for each pixel representing the day of the year that a part of the perimeter first caught fire[70]. Refer to the left panel in Figure 4.2 for an example of one of the Parks raster layers. The 30m x 30m pixels of this raster layer become our units of observation.

The data on LAT drops and daily wildfire growth are used together to construct our sample. We overlay the daily perimeters for each fire in our sample with the buffered LAT drops that define our

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[70] Parks 2014 refers to this as the "Day of Burning" raster.

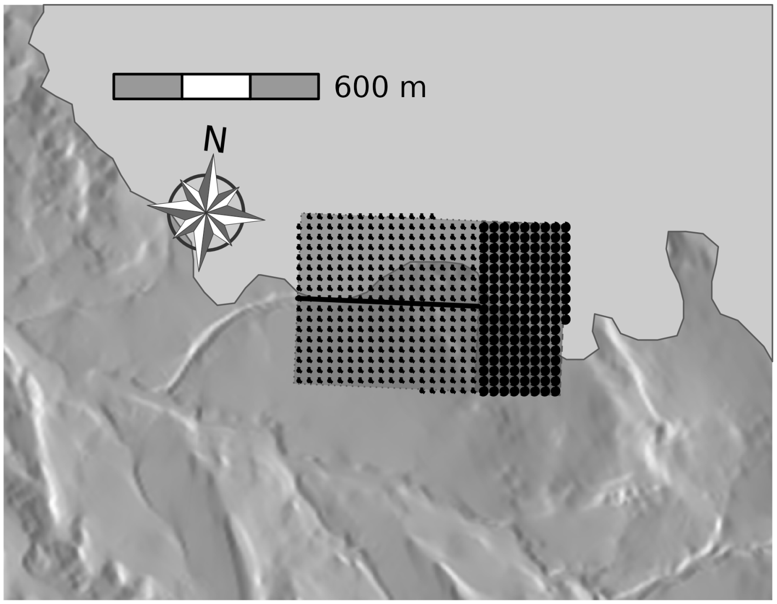

Figure 4.5: Example of a drop's treatment and control buffers broken into 30m x 30m cells.

treatment and control areas. We then extract all of the raster cells from the daily perimeters that are within the LAT drop buffers. Figure 4.5 provides an example; the treatment and control areas in Figure 4.3 are broken into a grid of 30m by 30m cells. These cells identify if the land around a LAT drop burned, and if so, how long it took to initially burn.

The day-of-burning raster layer (Parks 2014) is not just used to identify land that has burned from land that hasn't; we also use this layer to identify the pre-treatment units from the post-treatment units. After each LAT drop is buffered on both sides by 250 meters, we then identify which of the two buffers was the pre-treatment vs. post-treatment based on visual inspection in ArcGIS Pro with the daily wildfire rasters[71]. The daily spread pattern often indicates the direction the fire approached the drop from, revealing the land that was the most logical target for protection (post-treatment). We remove all contaminated control cells from the data; cells that were defined as controls due to their adjacency to a retardant drop, but are actually buffered by a different drop.

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[71] Originally, a program was written to identify what was pre-treatment vs. post-treatment based on several rule sets with GIS processing in R. However, due to the stochastic nature of wildfire growth on the sub-day level, it was difficult to determine what was truly the pre- vs. post-treatment using a programmatic approach. That necessitated a "coding by hand" method for defining treatment periods.

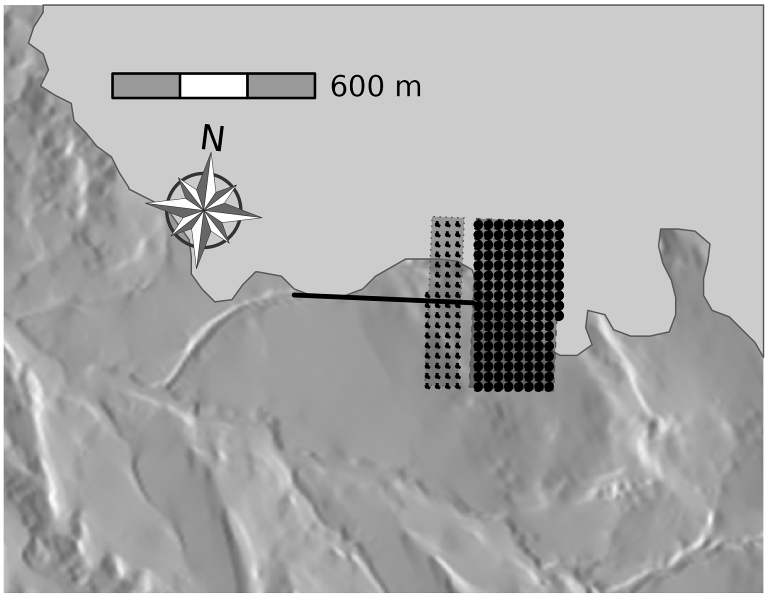

Figure 4.6: The area at the beginning of the drop is where treatment cells are pulled from for this analysis, as displayed above.

We employ a systematic approach to define the treatment (and control) areas associated with each LAT drop in the sample used for the spatial differences-in-differences (DiD) model. We clip each drop in our sample into a segment that is the first quarter of the drop's length. This is done to exploit the quasi-randomness in drop locations. The area protected by the middle of the drop was selected for treatment with intent, but the beginning of the drop is plausibly random[72]. The resultant line segment is then buffered by 250 meters on either side (refer back to Figure 4.3 for an example) to get the land we will be pulling cells from to define the treatment units. Figure 4.6 gives a visual depiction of the land we use to select treatment cells in the spatial DiD. We use all of the cells available in the 250-meter buffers, shown in Figure 4.5, for the RDD estimation.

We consider the aerial spread of LAT retardant after it is released when constructing our sample. After extracting a set of cells for each drop, we remove the ones that are directly adjacent to the retardant line. This accounts for the tendency of retardant to disperse in the air after it has been released from the plane, evidenced by Figure 4.7. The pink cloud following the airplane represents

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[72] The end of the drop is plausibly random as well, but there is more potential for measurement error using that space. There is evidence that pilots don't always close the doors on LATs upon running out of retardant.

an actual retardant drop, while the blue shows how that drop would be spatially represented in our data. These cells are excluded to mitigate the risk of misclassification of land as unprotected when, in reality, it may have been covered by retardant during the drop.

Figure 4.7: Physical dispersal pattern of LAT retardant drops (photo credit ABC News)

We include different wildfire outcomes in our data to use as dependent variables in our model. Our extensive margin model uses a binary indicator of a cell burning at any point in time following a retardant drop as the dependent variable in a linear probability model[73]. We use data from Monitoring Trends in Burn Severity (MTBS) for our intensive margin estimation in an OLS model. This dataset provides a spatial layer that measures burn severity post-wildfire in 30m by 30m cells. It serves as a reliable statistical indicator of a wildfire's destructive capacity in a given area and is the best available proxy for estimating damages from smoke or vegetative loss in that location. Our final dependent variable measures the ability of LATs to delay the spread of wildfire. For all

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[73] A logit model was estimated; it did not have substantively different results.

cells that burn, we measure the amount of time that passed following the retardant drop until the MODIS and VIIRS satellites first observed wildfire.

Weather is an important source of changes in wildfire behavior. We extract the weather at the time of the drop for each cell in our sample from Gridmet, a gridded dataset of daily weather. We extract values at the centroid of each cell for precipitation, temperature, wind speed, humidity, and PDSI.[74] Weather is an important determinant of wildfire growth (Abatzoglou and Kolden 2011); this information will capture weather's role in wildfire extent and severity. We also use this information to evaluate the heterogeneity of LAT suppression effectiveness in different weather conditions.

The type and concentration of vegetative fuels affect fire growth. The Anderson 13 fuels raster layer (Forest Service and Land Management 2020) is used to generate a measure of vegetative fuels in each cell. The available fuel types and concentration will be a primary determinant of a wildfire's extent and severity.

Burn probability and hazard potential are crucial factors that influence wildfire growth on the extensive and intensive margins. We extract a value for each cell from the Forest Service's burn probability raster layer (K. Short et al. 2016). The "burn probability" layer uses simulations of tens of thousands of hypothetical fire seasons based on varying weather, fire growth, and suppression strategy scenarios and is resolved in a 270m grid. A value for the wildfire hazard potential of each cell is also extracted into our data (Dillon and Gibertson-Day 2020). This layer is depicted at a 270-meter resolution and categorizes wildfire severity into five tiers of hazard potential. The burn probability information is included in the data to account for the base likelihood of a cell catching fire, while the wildfire hazard potential describes how severe a wildfire could get in a cell conditional on burning.

Terrain and slope are important determinants of wildfire severity (Holden and Jolly 2011). Topographical information for each land cell; elevation, slope, terrain ruggedness (TRI), and aspect; is extracted using the "elevatr" package in R at the same resolution as the day-of-burning raster

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[74] Palmer Drought Severity Index (PDSI) is a measure of drought conditions.

(30m). We transform asepct into a variable that describes the degree to which a cell faces the north vs. the south[75]. A value of -1 would mean a cell is angled to face due south, while 1 would mean it faces due north.

Table 4.1 contains summary statistics on key variables in our analysis; dependent and explanatory variables. More than half of the cells in our sample burned, evidenced by the mean of the "burned cell" variable in the first row. 25% of our sample are considered "treated" in this analysis.

Table 4.1: Summary statistics

Variable	Mean	Std. Dev.	Median	Min	Max	Count
Burned cell	0.59	0.49	1	0	1	52328
MTBS Burn Severity (1-4)	1.32	1.24	2	0	4	52328
Time until burn (hours)	49.2	130.08	0.24	0	888	17700
Cell in treatment area	0.49	0.5	0	0	1	52328
Pre-treatment cell	0.48	0.5	0	0	1	52328
Treatment cell	0.25	0.43	0	0	1	52328
Distance to drop (m)	145.04	61.52	145.86	35.03	250	52328
Number of drops						3014
Cells per drop						17.36

Figure 4.8 presents the balance of observables between the treatment and control units in our sample. The table does not suggest that there are any noticeable differences in the biophysical conditions leading to wildfire growth. If anything, the control units are marginally more susceptible to wildfire growth due to slightly higher values for terrain ruggedness, slope, fuel concentrations, and wildfire hazard potential. This table shows that the cells adjacent to a retardant drop are a valid counterfactual for wildfire growth; they are similar in observable characteristics to our treatment cells.

The sample used to produce estimates with our model is constructed from a bootstrapping process. Our full dataset contains roughly 52,328 cells from 3,014 drops, but only a subset of cells

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[75] South-facing slopes are more susceptible to wildfire because of the increased sun exposure (Zhai et al. 2023), which is why we control for aspect in the North-South direction but not East-West.

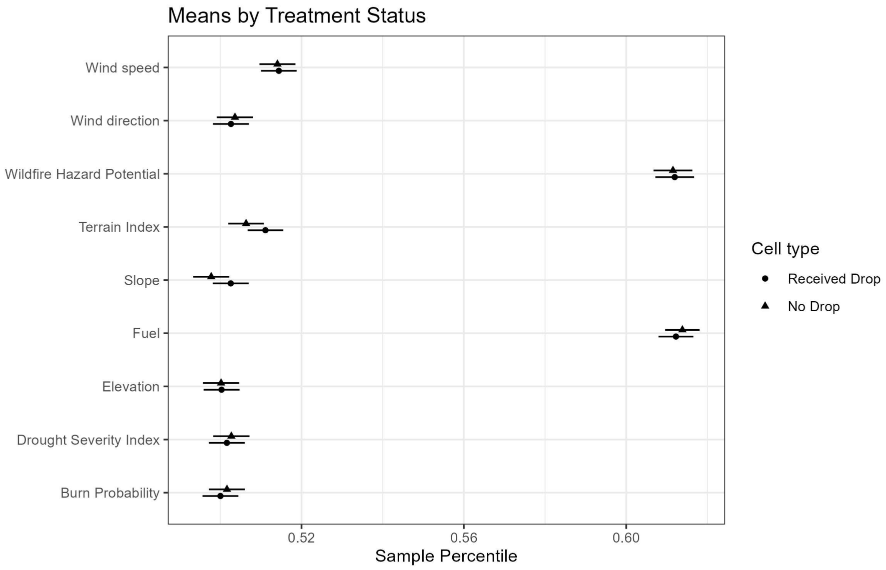

Figure 4.8: Balance of observables between treatment and control units

are used for each model estimation. We randomly select one point for each treatment group[76] per drop when we estimate our model.

We use a few different methods to pick the cells to represent the treatment and control areas. We produce estimates varying how the four points are chosen for each drop. The first method randomly chooses one cell for each treatment group, blind to their position relative to the drop. We then use a selection algorithm that ensures that pre/post-cells are paired based on distance/angle to ensure that we are not comparing wildfire outcomes for a cell in direct proximity to the retardant line with one that is much further removed. In this algorithm, treatment and control units do not necessarily have the same distance/angle measure. The second formal algorithm ensures that all four points have a similar distance and angle to the LAT drop. This process is bootstrapped (with replacement) a thousand times to create the sample we use to estimate LAT effectiveness.

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[76] Referring to Figure 4.3, we randomly select one point from A, B, C, and D for each iteration of the bootstrapping process.

4.4 Results

4.4.1 Difference-in-Difference model results

Table 4.2 contains the results for the linear probability model using a binary indicator for a cell burning as the dependent variable; this is the extensive margin impact of a retardant drop. The first column contains results for a model where all four treatment groups are selected at random without controls for any covariates. The second column also contains results for randomly selected cells but does control for other factors relevant to fire suppression, such as terrain or hazard potential. Column 3 holds results for a model estimated using the first selection algorithm; pre-treatment and post-treatment observations will have the same distance and angle to LAT drop, but not necessarily the treatment and control. Column 4 has results obtained using the selection algorithm that determines points in all four treatment groups based on a common distance and angle to the drop.

Column 1 of Table 4.2 shows that the likelihood of the fire spreading into a particular cell is decreased by 5.1 percentage points. The inclusion of controls decreases the magnitude of this effect to 5 percentage points. Once cells are paired with points that mirror them on the opposite side of the LAT drop, we find a statistically significant and negative effect of about 4.8 percentage points. That effect increases slightly to 5 percentage points once treatment points are also matched with control points by distance to the drop. Given that 59% of the cells in our sample end up catching fire, this implies that protection from wildfire by a retardant drop decreases the likelihood of a burn by 8.4%.

We test whether retardant drops can cause a reduction in flame intensity as the wildfire grows over it. Table 4.3 follows an identical column layout to Table 4.2 but uses MTBS's burn severity as the dependent variable. In the most basic sample without controls, we see that the coefficient on the drop treatment variable is -0.1. That effect attenuates when controls for other factors relevant to wildfire suppression strategy are included in our model, but increases in magnitude when selection algorithms are used to pair cells with one another. When the full selection algorithm is employed with controls, the coefficient on the drop treatment remains -0.1. This intensive margin treatment effect represents a 7.6% reduction on a mean burn severity of 1.32.

Table 4.2: Dependent Variable - Binary indicator of a cell burning after a drop

	(1)	(2)	(3)	(4)
Drop Treatment	-0.051***	-0.05***	-0.048***	-0.05***
	(0.00)	(0.00)	(0.00)	(0.00)
Fuel concentrations (1 - 12)		1.428***	1.439***	1.463***
		(0.004)	(0.004)	(0.004)
Slope		0.001***	0***	0.001***
		(0.00)	(0.00)	(0.00)
Burn Probability		-2.278***	-2.275***	-2.337***
		(0.016)	(0.018)	(0.017)
Temperature (C)		0.004***	0.004***	0.004***
		(0.00)	(0.00)	(0.00)
Wind Speed (m/s)		0.022***	0.02***	0.021***
		(0.00)	(0.00)	(0.00)
Wind Direction (degrees)		0***	0***	0***
		(0.00)	(0.00)	(0.00)
PDSI		-0.001***	-0.002***	-0.001***
		(0.00)	(0.00)	(0.00)
Elevation (1000m)		0***	0***	0***
		(0.00)	(0.00)	(0.00)
Terrain Ruggedness Index (m)		-0.102***	-0.102***	-0.104***
		(0.00)	(0.00)	(0.00)
WHP (1 - 5)		0.013***	0.012***	0.012***
		(0.00)	(0.00)	(0.00)
Controls?	No	Yes	Yes	Yes
Selection Algorithm #1	No	No	Yes	Yes
Selection Algorithm #2	No	No	No	Yes
Observations	9325	9325	9055	9206
Dep. Var Mean	0.59	0.59	0.59	0.59

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

The final measure of effectiveness we consider is the ability of LATs to delay the spread of wildfire. Table 4.4 shows estimates of our model using a subset of our LAT drops that burned over. The dependent variable is the amount of time following the LAT drop until a cell first burned. In Column 1, we can see that land that was protected by a retardant drop took 5.76 more hours to catch fire than adjacent land that was left unprotected. In our full specification, we find that land protected by a drop takes four more hours to burn.

The signs and significance of the coefficients on the covariates displayed in Tables 4.2, 4.3, and 4.4 match ecologic intuition. We observe a negative sign on "Fuels" in Table 4.2, but a positive one in Table 4.3. Lower values of this variable are consistent with grass-type fuels where fire spreads quickly but at a lower intensity, while higher levels of "Fuels" represent denser canopy-type vegetation or "slash" that provides dense fuel for a growing wildfire[77]. "Burn Probability" is associated with an increased likelihood and intensity of burn, while wildfire hazard potential (WHP) is only associated with an increased intensity. Drought conditions (PDSI) and temperature both increase wildfire growth on extensive and intensive margins.

4.4.2 Heterogeneity analysis

Results from our baseline estimation show that large airtankers (LATs) are effective at limiting the physical extent of wildfire, delaying its spread, and diminishing the intensity of flame as it grows. It's likely that the effectiveness of LAT suppression is contingent on the landscape that is being dropped upon. In Tables 4.5 through 4.11, we analyze what factors are likely to lead to a LAT drop being more effective at reducing the extent of a wildfire's spread or diminishing its burn intensity. For this draft of the paper, the factors we analyze will be (i) vegetative fuel types, (ii) slope, (iii) aspect, (iv) wind speed & angle, (v) aircraft type (VLAT vs. classic LAT), and (vi) the retardant lines used in concert with other forms of containment.

Table 4.5 contains results from a model that interacts LAT drop treatment with an indicator for the type of vegetative fuels that it was protecting. Fuels are classified into one of three groups

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[77] The finding on the "time until burn" model is consistent with this as well, where higher values take longer to initially catch fire.

Table 4.3: Dependent Variable - MTBS Burn Severity measured post-fire

	(1)	(2)	(3)	(4)
Drop Treatment	-0.1***	-0.09***	-0.11***	-0.1***
	(0.00)	(0.00)	(0.00)	(0.00)
Fuels (1 - 12)		-8.23***	-7.85***	2.28***
		(0.12)	(0.13)	(0.04)
Slope		-0.02***	-0.02***	-0.02***
		(0.00)	(0.00)	(0.00)
Burn Probability		-8.23***	-7.85***	-8.32***
		(0.12)	(0.13)	(0.13)
Temperature (C)		0.01***	0.01***	0.01***
		(0.00)	(0.00)	(0.00)
Wind Speed (m/s)		0.07***	0.07***	0.08***
		(0.00)	(0.00)	(0.000)
Wind Direction (degrees)		0***	0***	0***
		(0.00)	(0.00)	(0.00)
PDSI		0***	0***	0
		(0.00)	(0.00)	(0.00)
Elevation (1000m)		0***	0***	0***
		(0.00)	(0.00)	(0.00)
Terrain Ruggedness Index (m)		-0.15***	-0.16***	-0.16***
		(0.00)	(0.00)	(0.00)
WHP (1 - 5)		0.02***	0.01***	0.02***
		(0.00)	(0.00)	(0.00)
Controls?	No	Yes	Yes	Yes
Selection Algorithm #1	No	No	Yes	Yes
Selection Algorithm #2	No	No	No	Yes
Observations	9325	9325	9055	9206
Dep. Var Mean	1.32	1.32	1.32	1.32

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

Table 4.4: Dependent Variable - Time until burn

	(1)	(2)	(3)	(4)
Drop Treatment	5.76***	4.32***	9.12***	4.08***
	(0.00)	(0.00)	(0.05)	(0.03)
Fuels (1 - 12)		1018.32***	966.96***	488.16***
		(7.44)	(7.92)	(1.92)
Slope		7.92***	7.92***	7.68***
		(0.00)	(0.00)	(0.00)
Burn Probability		1018.32***	966.96***	1021.68***
		(7.44)	(7.92)	(8.16)
Temperature (C)		-4.8***	-4.56***	-4.8***
		(0.00)	(0.00)	(0.00)
Wind Speed (m/s)		-22.08***	-21.36***	-22.32***
		(0.00)	(0.00)	(0.00)
Wind Direction (degrees)		-0.24***	-0.24***	-0.24***
		(0.00)	(0.00)	(0.00)
PDSI		-3.36***	-3.36***	-3.36***
		(0.00)	(0.00)	(0.00)
Elevation		0***	0	0***
		(0.00)	(0.00)	(0.00)
Terrain Ruggedness Index (m)		-36***	-35.04***	-37.44***
		(0.24)	(0.24)	(0.24)
WHP (1 - 5)		3.12***	2.64***	3.12***
		(0.00)	(0.00)	(0.00)
Controls?	No	Yes	Yes	Yes
Selection Algorithm #1	No	No	Yes	Yes
Selection Algorithm #2	No	No	No	Yes
Observations	3199	3197	3098	3150
Dep. Var Mean	49.2	49.2	49.2	49.2

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

Table 4.5: Heterogeneity of LAT suppression effectiveness by vegetative fuel types

	(1) Burned cell?	(2) Burn Severity	(3) Time until burn
Drop Treatment * Shrubs	-0.014***	-0.032***	13.56***
	(0.000)	(0.002)	(0.36)
Shrubs	0.23***	0.992***	-13.536***
	(0.001)	(0.002)	(0.408)
Drop Treatment * Trees	0.001	0.009***	4.152***
	(0.001)	(0.002)	(0.336)
Trees	0.513***	2.466***	-1.536**
	(0.001)	(0.004)	(0.744)
Drop Treatment	-0.047***	-0.056***	-0.456***
	(0.001)	(0.001)	(0.144)
Controls?	Yes	Yes	
Selection Algorithm #1	Yes	Yes	Yes
Selection Algorithm #2	Yes	Yes	Yes
Observations	9325	9325	3199
Dep. Var Mean	0.59	1.32	49.2

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

based on the Anderson 13 Fuels model (Forest Service and Land Management 2020): grasses, shrubs, or trees[78]. The omitted category in this model is grass-type fuels. Each column of Table 4.5 contains a model with a different dependent variable; all coefficients presented come from models that control for other factors relevant to wildfire suppression and use the second selection algorithms for pairing pre-treatment points with post-treatment points, as well as control points.

Column 1 informs how LAT drops may be more or less effective at curbing the spread of a wildfire's spatial extent. Coefficient estimates on the fuel type indicator variables have the expected signs and significance levels; wildfire is more likely to spread into a cell with shrubs or trees than grass. We don't observe a statistically significant effect on the effectiveness of LATs in reducing the spread of fire into trees. LAT drops are more effective on the extensive margin when dropping in shrubs (1.4 percentage points).

Column 2 contains intensive margin estimates. The magnitude of the coefficient on the indicator for trees matches ecological intuition; wildfire burns more intensely in denser canopy-type fuels. Shrubs also burn more intensely than grass, the omitted fuel. Similar to Column 1, the heterogeneity estimates show that LAT drops are more effective on the intensive margin in shrubs than they are in grass or trees

The heterogeneity of LAT effectiveness at delaying the spread of wildfire is shown in Column 3. The negative coefficient on the shrub and tree variables shows that fire spreads faster when it doesn't have to burn over a retardant drop. The indicators for trees and shrubs have coefficients with a magnitude that suggests fire tends to spread at a slower rate in denser tree vegetation. The negative sign on the baseline treatment variable shows that LATs aren't effective at slowing the fire's spread in grass. LATs are most effective at slowing the spread of wildfire in shrubs, but retardant also inhibits spread when dropped on trees.

Table 4.6 contains the results from a heterogeneity analysis where we interact the drop treatment with a continuous variable representing the slope of the land protected. The columns in Table

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[78] Another classification within the Anderson 13 fuels model is "slash", but none of the retardant drops in our sample land on slash fuel.

Table 4.6: Heterogeneity of LAT suppression effectiveness by slope

	(1) Burned cell?	(2) Burn Severity	(3) Time until burn
Drop Treatment * Slope	-0.044***	-0.005	0.816
	(0.002)	(0.005)	(0.864)
Slope	1.321***	5.634***	428.904***
	(0.004)	(0.012)	(1.824)
Drop Treatment	-0.037***	-0.057***	1.128***
	(0.001)	(0.001)	(0.264)
Controls?	Yes	Yes	Yes
Selection Algorithm #1	Yes	Yes	Yes
Selection Algorithm #2	Yes	Yes	Yes
Observations	9058	9058	3099
Dep. Var Mean	0.59	1.32	49.2

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

4.6 follow the same layout as Table 4.5 regarding the dependent variables. The coefficient estimate on the slope variable shows that fire has a tendency to grow in intensity as it moves uphill, as evidenced by the second row of Column 2. This is to be expected, given the physical and chemical properties of wildfire. We don't find that slope has an impact on the intensive margin effectiveness of LAT suppression.

Slope only changes the effectiveness of LAT suppression on the extensive margin. A retardant drop on perfectly flat land would reduce the likelihood of wildfire spread by 3.7 percentage points. The coefficient on the interaction term shows that this effectiveness increases with slope. A drop on land that is at a 20% grade will reduce the likelihood of wildfire spread by 4.6 percentage points. This is a 7.6% decline in the mean rate of burning for our cells.

Table 4.7 shows results from a model analyzing the heterogeneity of LAT effectiveness based on the aspect of terrain in the North-South direction. Aspect is a continuous variable bound between -1 and 1. A value of -1 means that a cell of land is angled to face due South, a value of 1 means it faces due north, and a value of 0 would indicate it faces exactly east or west. As expected,

Table 4.7: Heterogeneity of LAT suppression effectiveness by aspect (North-South)

	(1) Burned cell?	(2) Burn Severity	(3) Time until burn
Drop Treatment * Aspect (N-S)	-0.012***	-0.024***	4.752***
	(0.001)	(0.001)	(0.264)
Aspect (N-S)	-0.003***	0.047***	-2.04***
	(0)	(0.001)	(0.12)
Drop Treatment	-0.048***	-0.057***	0.72***
	(0)	(0.001)	(0.12)
Controls?	Yes	Yes	Yes
Selection Algorithm #1	Yes	Yes	Yes
Selection Algorithm #2	Yes	Yes	Yes
Observations	9058	9058	3102
Dep. Var Mean	0.59	1.32	49.2

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

the coefficient estimate on "Aspect (N-S)" in Column 1 indicates that wildfire is more likely to increase its spread on south-facing slopes. Perhaps not to be expected, wildfire burns at a lower intensity on the same slopes, indicated by the positive coefficient estimate on aspect in Column 2.

We find that LATs are more effective at suppressing wildfire growth on south-facing slopes across all three dimensions we analyze. It appears from the coefficient estimates on the interaction term in Column 1 that LAT drops on slopes facing South would reduce the likelihood of wildfire by 6.3 percentage points. Column 2 suggests that LAT retardant drops on south-facing slopes reduce the MTBS burn severity by 0.034. That is a 1.8% reduction in intensity relative to a fire burning unfettered by retardant on an E-W slope.

Our results indicate that LAT suppression is less effective as winds get stronger. The coefficient estimate on the drop treatment variable in the third row of Table 4.8 indicates that a LAT drop in an environment with no wind would reduce the likelihood of wildfire burning on the protected land by 8.1 percentage points. It would decline in effectiveness by 1 percentage point for each unit (m/s)

Table 4.8: Heterogeneity of LAT suppression effectiveness by wind speed

	(1) Burned cell?	(2) Burn Severity	(3) Time until burn
Drop Treatment * Wind speed (m/s)	0.01***	0.033***	-7.368***
	(0.000)	(0.001)	(0.12)
Wind speed (m/s)	0.014***	0.049***	-16.776***
	(0.000)	(0.000)	(0.072)
Drop Treatment	-0.081***	-0.17***	-0.984***
	(0.001)	(0.002)	(0.48)
Controls?	Yes	Yes	Yes
Selection Algorithm #1	Yes	Yes	Yes
Selection Algorithm #2	Yes	Yes	Yes
Observations	9058	9058	3102
Dep. Var Mean	0.59	1.32	49.2

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

increase in wind speed. There is a similar pattern with the intensive margin measure of suppression effectiveness.

We complement Table 4.8 with a model that analyzes the heterogeneity in LAT effectiveness based on the angle of the wind relative to the drop. The angle is determined based on the measure of prevailing wind direction (from Gridmet) on the day the wildfire first entered a LAT drop's pre-treatment buffer. We separate the angle is separated into three distinct bins: 0 to 30 degrees, 30 to 60, and 60 to 90 degrees. We then interact each bin with the measure of LAT treatment, with the omitted category being the middle bin (30 to 60 degrees).

The results for this model are presented in Table 4.9. The first row shows how LATs scale in effectiveness when the wind is most acute relative to the retardant line, while the third row does so for wind that is most orthogonal to the line. Our coefficients in Column 1 show that LATs aren't more effective at reducing the likelihood of wildfire in the post-treatment area depending on the angle of the wind. LATs appear to be more effective at delaying the spread of fire when the wind approaches at a low angle (Column 3). The effectiveness of LAT drops at delaying the spread of

Table 4.9: Heterogeneity of LAT suppression effectiveness by angle of prevailing wind direction to the retardant drop

	(1) Burned cell?	(2) Burn Severity	(3) Time until burn
Drop Treatment * Wind angle (0 - 30)	0.009	-0.019***	4.992***
	(0.023)	(0.002)	(0.288)
Wind angle (0 - 30)	0.014***	0.008***	-5.136***
	(0.000)	(0.001)	(0.168)
Drop Treatment * Wind angle (60 - 90)	0.001	-0.006***	-0.024
	(0.001)	(0.002)	(0.312)
Wind angle (60 - 90)	0.018***	-0.013***	-7.056***
	(0.000)	(0.001)	(0.168)
Drop Treatment	-0.065***	-0.069***	0.120
	(0.000)	(0.001)	(0.216)
Controls?	Yes	Yes	Yes
Selection Algorithm #1	Yes	Yes	Yes
Selection Algorithm #2	Yes	Yes	Yes
Observations	9307	9307	3209
Dep. Var Mean	0.59	1.32	49.2

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

wildfire does not change from its baseline level when the retardant line is orthogonal to the wind. The results in Column 2 show that retardant drops are about 1.5% more effective at reducing the intensity of flames with low-angled wind than their baseline level, given a mean burn severity of 1.32. They are 0.5% more effective when the wind is orthogonal to the retardant.

Table 4.10: Heterogeneity of VLAT suppression effectiveness

	(1) Burned cell?	(2) Burn Severity	(3) Time until burn
Drop Treatment * VLAT	-0.049***	-0.074***	37.992***
	(0.002)	(0.005)	(0.648)
VLAT	-0.178***	-0.387***	40.728***
	(0.002)	(0.004)	(0.48)
Drop Treatment	-0.048***	-0.058***	0.72***
	(0.000)	(0.001)	(0.12)
Controls?	Yes	Yes	Yes
Selection Algorithm #1	Yes	Yes	Yes
Selection Algorithm #2	Yes	Yes	Yes
Observations	9057	9057	3100
Dep. Var Mean	0.59	1.32	49.2

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

Not all large airtankers have an identical physical capacity to release fire retardant for wildfire suppression. Certain aircraft have been labeled "very large airtankers" (VLATS) because their tanks can hold over twice as much fire retardant. Our *a priori* hypothesis is that VLATS should be more effective than LATs at reducing the extent of a wildfire's spread and diminishing the severity of burn. Table 4.10 confirms that hypothesis, finding that VLATs are more effective at fire suppression on both outcomes of interest. VLATs are 4.9 percentage points more likely to halt the spread of a fire (Column 1) and delay the spread of wildfire by 38 more hours (Column 3). We also find that VLATs are more than twice as effective as LATs at reducing flame intensity (Column 2).

Table 4.11: Heterogeneity of LAT suppression effectiveness by the presence of other containment line

	(1) Burned cell?	(2) Burn Severity	(3) Time until burn
Drop Treatment * Other containment	0.02***	0.098***	30.984***
	(0.00)	(0.00)	(0.72)
Other containment	-0.061***	-0.098***	76.248***
	(0.001)	(0.002)	(0.408)
Drop Treatment	-0.05***	-0.066***	0.768***
	(0.00)	(0.00)	(0.00)
Controls?	Yes	Yes	Yes
Yes			
Selection Algorithm #1	Yes	Yes	Yes
Selection Algorithm #2	Yes	Yes	Yes
Observations	9057	9057	3098
Dep. Var Mean	0.59	1.32	49.2

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

The final element of heterogeneity considered in this analysis is retardant drops that are complemented by other forms of suppression effort, such as hand-dug lines by firefighters or containment lines created by dozers. Table 4.11 contains results for a model that interacts the retardant treatment with an indicator for the drop being in proximity to another containment line. It's clear that these other forms of suppression effort are correlated with reduced likelihood and intensity of wildfire growth based on the coefficient estimates in the second row. LATs are less effective at (i) halting the spread and (ii) diminishing the intensity of wildfire when used near other forms of containment. We do find, however, that LATs are more effective at delaying the spread of wildfire by about 31 more hours when used in concert with ground resources compared to its neighboring land that also received another type of containment.

4.4.3 Robustness

Our spatial difference-in-differences estimates found that LAT retardant drops are generally effective at limiting the extent of wildfire growth, delaying its spread, and diminishing the intensity of its flames. We evaluate the robustness of that finding with a spatial regression discontinuity. In this econometric setup, we compare wildfire outcomes on the land right before the fire interacts with the drop with outcomes just after the fire passes over the drop.

This natural experiment in this identification strategy relies on the assumption of random treatment assignment across different observable wildfire-relevant characteristics. It would be problematic for this identification strategy if LAT drops were categorically released on top of steep slopes or as vegetation increased in concentration. We test the validity of this assumption in Figures 4.9 and 4.10 by plotting different factors relevant to wildfire suppression over our running variable (distance to drop). Figure 4.9 shows that we aren't sorting drops on the basis of fuel concentrations or slope, two factors directly observable to a pilot or IC. Figure 4.10 shows similar plots for two factors that are primarily observable with GIS data: wildfire hazard potential and burn probability. We don't observe any sorting across these factors either.

Now that we are certain LAT resources aren't being spatially allocated as a function of other features of the land, we can pursue estimation of this effect through an RDD. Figure 4.11 allows us to visually inspect if there is an extensive margin treatment effect. The plot shows that there is a clear discontinuity at distance 0, meaning there should be a clear treatment effect for the large airtanker (LAT) drop.

Building on this qualitative visual assessment, we estimate this treatment effect using quantitative evaluation. RDD estimates are produced using the "rdd_reg_lm" command in R from the "rddtools" package. Each regression separates out observations into three distinct bins; estimates are produced using bandwidths of 250 meters and 150 meters on either side of the drop. Cells are grouped into three distinct bins to determine the treatment effect.

Table 4.12 contains results for the sharp regression discontinuity model. Columns 1 through 3 contain coefficient estimates for the extensive margin treatment effect; results from Column 1 come from a model that uses a bandwidth of 250 meters around the drop and no controls. We include controls in the model presented in Column 2. Column 3's results come from a model using a tighter bandwidth of 150 meters to determine the treatment effect.

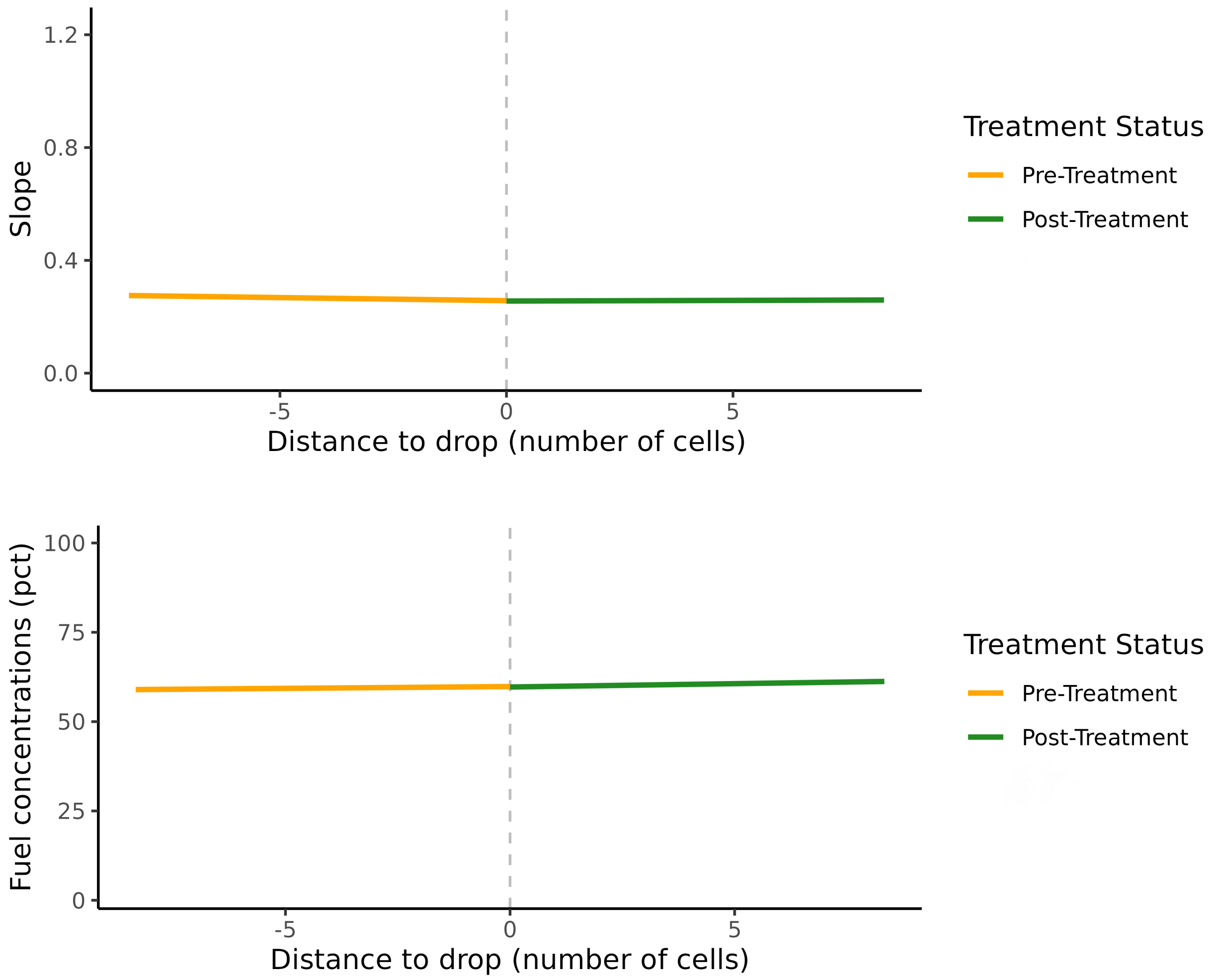

Figure 4.9: Directly observable wildfire-relevant factors by distance to LAT drop.

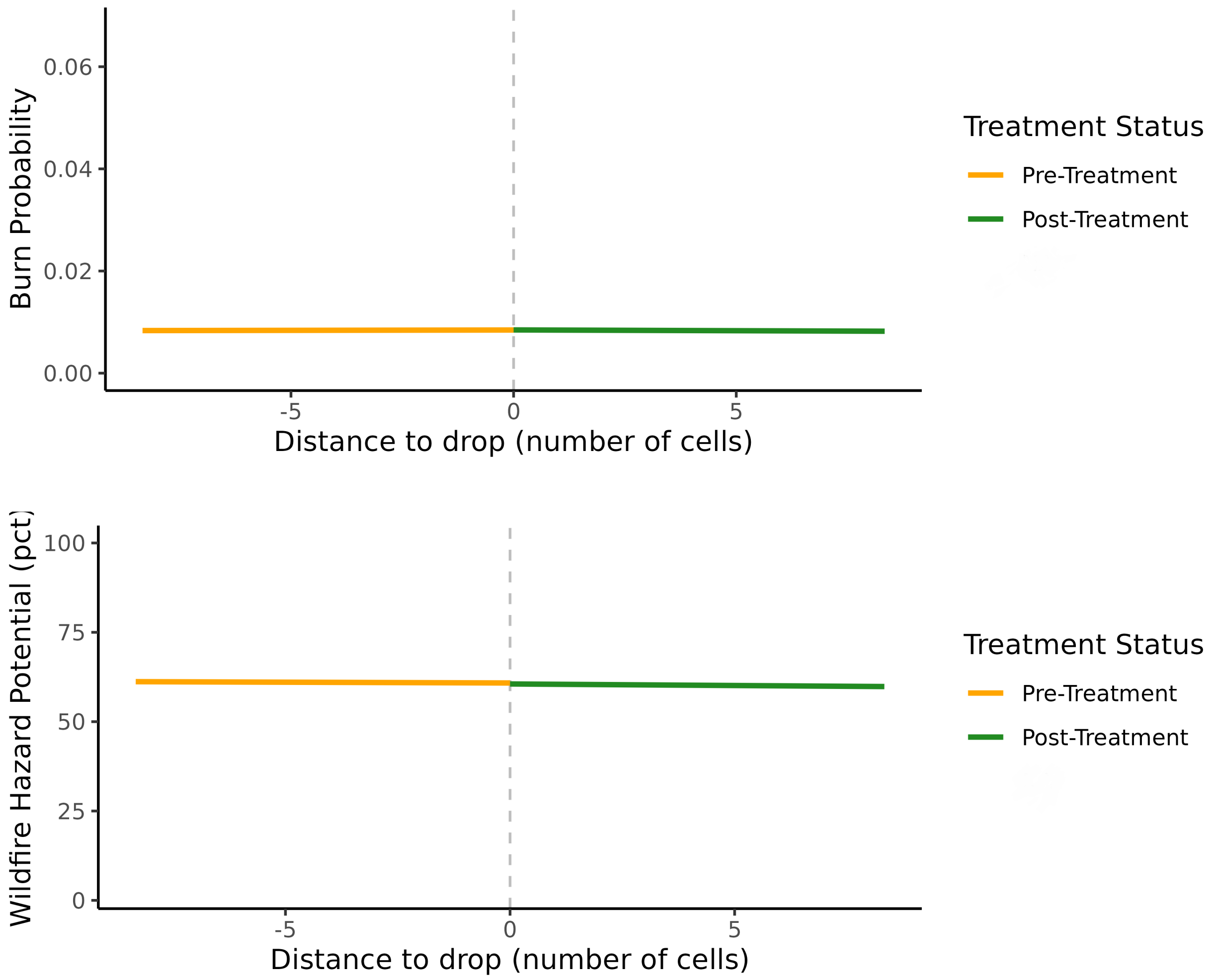

Figure 4.10: Indirectly observable wildfire-relevant factors by distance to LAT drop.

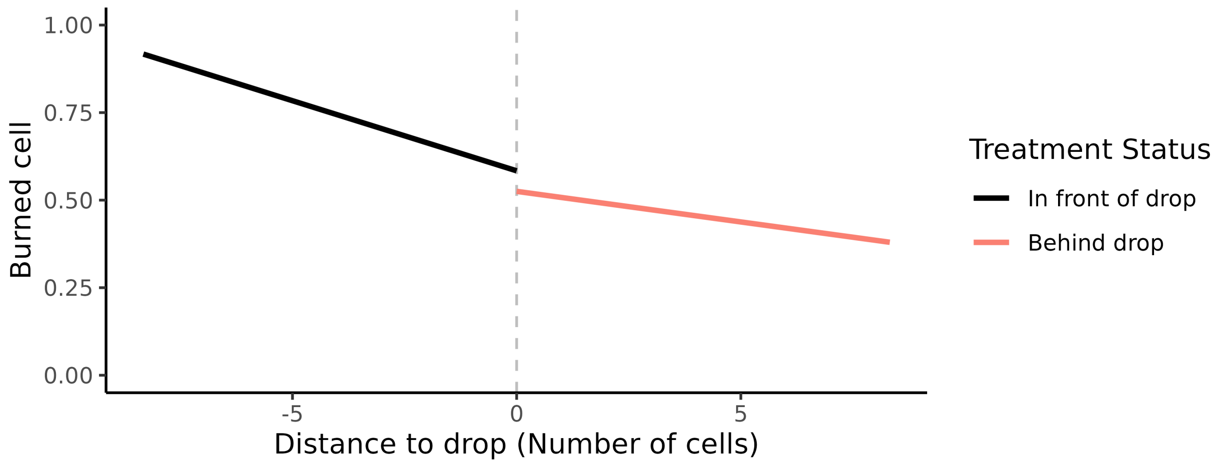

Figure 4.11: Share of cells at each distance that burned

According to the coefficient estimate in Column 1, LAT drops reduce the likelihood of wildfire spreading into the area behind it by about 12.8 percentage points. That estimate increases slightly in magnitude when we control for other factors relevant to wildfire suppression strategy (also statistically significant). That is a 21% reduction on the mean likelihood of a cell catching fire. That treatment effect increases to 15.8 percentage points when we tighten the bandwidth of observations to those within 150 meters of the drop.

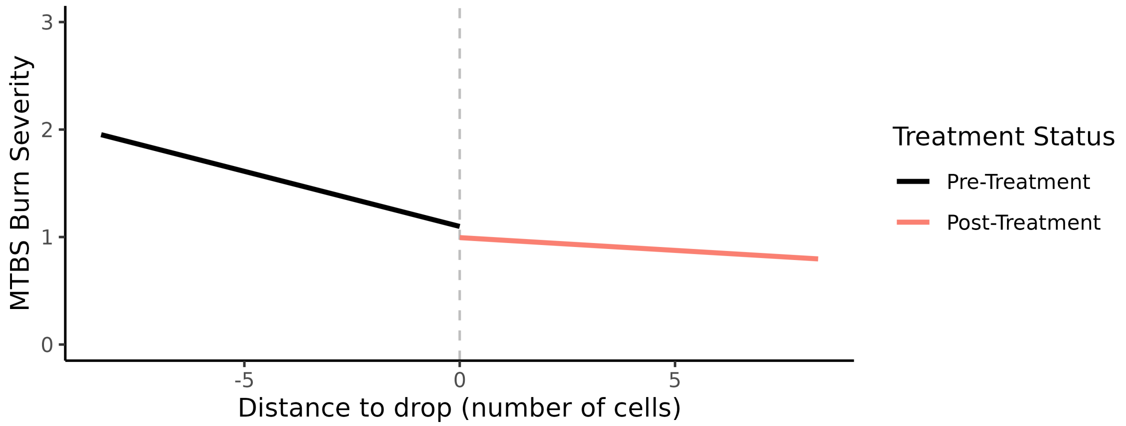

Figure 4.12: Average MTBS "burn severity" (converted to percentile rank) at each distance that burned

Figure 4.12 shows that there is also a clear discontinuity on the intensive margin impact around the cutoff of zero, as measured by the MTBS burn severity. Columns 4 through 6 of Table 4.12

follow an identical pattern to Columns 1 through 3, but replace the dependent variable with the intensive margin measure of wildfire severity. Before controlling for other factors considered in a wildfire suppression strategy, we estimate that LATs reduce the intensity of a wildfire's burn in a particular cell by a measure of -.2417. With an average burn severity value of about 1.32, that represents about an 18% reduction on the mean wildfire severity. This effect is robust to the inclusion of controls and varying the size of the bandwidth.

Table 4.12: Estimation of LAT drop treatment effectiveness using Regression Discontinuity (RDD)

Variables	(1) Did cell burn?	(2) Did cell burn?	(3) Did cell burn?	(4) Burn severity	(5) Burn severity	(6) Burn severity
Drop Treatment	-0.1276***	-0.1282***	-0.1576**	-0.2417***	-0.2442***	-0.2392***
	(0.0146)	(0.0146)	(0.0644)	(0.0374)	(0.0373)	(0.0902)
Observations	25607	25604	13325	25607	25604	13325
Treated Observations	12921	12918	6701	12921	12918	6701
Controls?	No	Yes	Yes	No	Yes	Yes
Bandwidth size	250m	250 m	150 m	250 m	250 m	150 m

Standard errors in parentheses.

4.5 Cost-Effectiveness

We have estimated parameters for the suppression effectiveness of large airtankers (LATs); we now have the necessary information to develop a measure of cost-effectiveness for each LAT drop. There are many potential benefits of preventing the spread of wildfire onto a particular piece of land. Some examples are the decrease in economic damages due to the reduction in smoke, the avoided harm to watersheds or ecosystem services, or the reduced risk to firefighters. Given the stated preferences of incident management teams from the AFUE study (U.S. Forest Service 2020), we are going to focus on the cost-effectiveness of LAT drops based on the avoided damage to homes or buildings from the wildfire.

Unfortunately, the ATUs mounted in LATs don't record an explicit cost measure for each retardant drop. We are able to calculate that cost using a random forest model with one year of restricted data from the Forest Service on daily aircraft suppression expenditures. Drops are collapsed to the day-fire-plane level, then combined with one year of daily aircraft expenditures. The random forest model is trained to predict the total suppression costs[79] for airplane p as a function of the total volume of fire retardant (TotalGal_{pd}) and number of drops released on day d, as well as the manufacturer & model of aircraft. That random forest model is then used to predict the daily costs for all of the airplanes ($\hat{\text{PC}}_{pd}$) that released drops in our sample, including the years we don't have aviation expenditure data. These daily airplane cost predictions are merged into our drops data, then a per-drop cost is calculated as a function of the amount of retardant a plane released in drop i (Gal_i) -

$$\text{Costs}_i = \left(\frac{\text{Gal}_i}{\text{TotalGal}_{pd}}\right)\hat{\text{PC}}_{pd} \tag{4.3}$$

After estimating a cost for all retardant drops using the random forest model, we can move forward with calculating the cost-effectiveness for each drop i based on the assets it protects. That measure takes the following form:

$$\text{Cost Effectiveness}_i = \frac{\text{Costs}_i}{\rho(\text{Assets}_i) - (1-\rho)(\hat{\text{Assets}_i})} \tag{4.4}$$

Costs_i is the predicted cost of a drop coming from the random forest model. ρ represents the likelihood that a retardant drop is fully effective at holding out wildfire from the land being defended; $(1-\rho)$ is the likelihood of the drop being completely ineffective. Assets_i is a measure of assets/resources that a retardant drop is protecting from the wildfire while $\hat{\text{Assets}_i}$ is a measure of those same assets in the event the wildfire burns over the drop. We will only be considering the extensive margin suppression effectiveness of LATs. Because of that, we will assume that $\hat{\text{Assets}_i}$ is 0 in the event that a retardant drop was ineffective at defending the land from the wildfire.

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[79] This does not include availability costs, which are essentially the fixed costs billed to a contractor for keeping an aircraft on standby to a fire.

There are many different types of assets that a LAT drop could protect; we focus on the cost-effectiveness of protecting homes and/or buildings for now[80]. The denominator of our cost-effectiveness calculation will be the number of homes that fall in the 250-meter post-treatment buffer of a drop. It's not straightforward to determine which homes were targeted for protection by a LAT drop, so we focus our calculation on the homes that appear to be direct recipients of suppression effort. This strict limitation on the number of homes considered will lead us to calculate LAT drops to be less cost-effective than a measure that uses a more generous definition of structures protected.

Table 4.13 contains estimates for the cost-effectiveness of our drops based on how many homes they were able to protect. For this cost-effectiveness calculation, we parameterize ρ using the results from the vegetative fuel-type heterogeneity in Table 4.5. we find that, of the 297 drops in our sample that were clearly intended for point protection, we spent about $85,910 per home/structure defended. Figure 4.13 contains a histogram of the cost-effectiveness measure. It appears that wildfire incident managers are generally cost-effective with their drops. However, some drops in our sample that were placed in the vicinity of homes were not used efficiently for point protection; their cost-effectiveness calculation was over $200,000 per home defended.

Table 4.13: Drop Cost Effectiveness Summary

Sample	Mean	Q1 (25th percentile)	Q3 (75th percentile)	Number of Drops	Number of Fires	Buildings per drop
All Drops	85.91	27.43	113.78	297	67	2.96
2017 Drops	68.88	23.78	89.67	128	31	3.15
2018 Drops	100.61	32.28	141.27	156	32	2.87
2019 Drops	76.82	17.92	91.11	13	4	2.08

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[80] Eventually, this analysis will be scaled up to consider other types of values, such as timber, ecosystem services, or clean water. We will also include intensive margin parameters in the cost-effectiveness calculation, as a lower-intensity fire could induce lower economic damages depending on the protected asset.

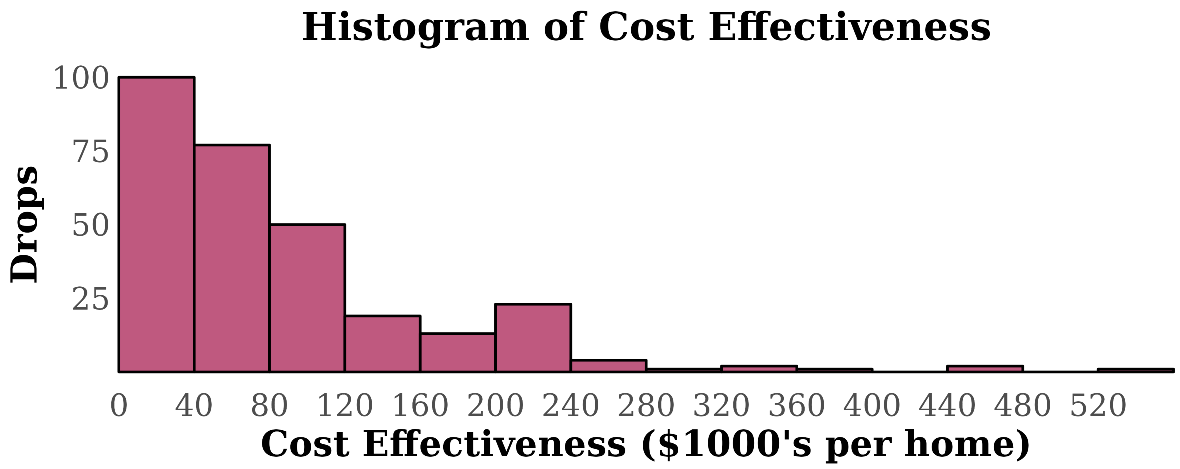

Figure 4.13: Density of drop cost effectiveness measures

4.6 Discussion

The estimates from our spatial difference-in-differences model support the use of large air-tankers (LATs) for suppression strategies outside of those that have been prioritized by incident managers (ICs) in the past (U.S. Forest Service 2020). We provide a key insight for the management of LATs for wildfire suppression. LATs may have significant benefits to provide to wildfire management through their ability to effectively diminish the intensity of flames. ICs could plan ahead (potentially by using a tool like PODS (Thompson, Gannon, Caggiano, et al. 2020)) and use LATs to help control the intensity of flames to a desirable level, aiding them in pseudo-selectively treating fuel loads that are in need of thinning. A cost-effectiveness measure tailored for intensive margin outcomes would better inform the ideal times to use LATs for this objective.

We derive extensive margin coefficient estimates from our spatial RDD model that suggest LAT retardant drops reduce the likelihood of wildfire spreading by 20-25%. This is comparable to Gannon, Wei, et al. 2023's baseline finding that 28% of fuel breaks successfully held back wildfire. Our spatial DiD model provides coefficient estimates on the extensive margin that are smaller in magnitude, suggesting that LAT suppression reduces the likelihood of fire spreading by 8%. This result is similar to Gannon, Wei, et al. 2023's finding that 13% of fuel breaks that aren't complemented with other types of containment successfully held out wildfire.

The extensive and intensive margin coefficients we estimate in our spatial regression discontinuity approach (Table 4.12) are larger in magnitude than those from our spatial difference-in-differences models (Tables 4.2 - 4.3). This suggests that fire is not systematically being pushed into our control areas in the spatial difference-in-differences estimation. As described in the Methods Section, if fire was frequently pushed from the area just in front of the retardant line into the control space adjacent to it, that would lead us to overestimate the effectiveness of LATs. However, we find that the coefficient estimates increase when we don't use the space next to the drop as the control area. Taken together, the RDD's sharp treatment effect (Wuepper and Finger 2023) and the spatial DiD's average treatment effect show that LAT suppression is effective on both extensive and intensive margins.

Our estimates for the heterogeneity of LAT suppression effectiveness support targeting land covered with shrub-type vegetation. There is evidence from land managers that LATs are relied upon heavily in fires in these types of fuels, as that is where they believe them to have a comparative advantage. LATs were found to be the most effective at delaying the spread of fire on all three outcomes (extensive, intensive, delaying spread) according to Table 4.5.

LATs could be useful to mission objectives in other types of fuel besides shrubs. Our results show that retardant drops are effective on all three margins when dropped on trees. This result supports incident managers that choose to use LATs to suppress fire in locations that pose a greater risk to on-the-ground resources like firefighters. LATs are also effective at halting wildfire spread and reducing intensity when dropping on grass, but they do not delay its spread. This is an intuitive finding, as there is less surface area on grass fuels for retardant to cover. If a LAT drop is unable to contain the spread of fire in grass, additional suppression tactics may be needed to reinforce containment efforts and prevent further fire growth.

There are important operational takeaways from this research informing how to maximize LAT suppression effectiveness, beyond the biophysical conditions of the land. We find that LAT drops used (i) with other types of containment and (ii) layered with other drops (Table C2 in the Appendix) only become more effective at delaying the fire's spread. These results suggest that placing a retardant line near existing containment would aid significantly in point protection but not other suppression strategies.

The LAT cost-effectiveness metric we developed could be used by ICs to inform suppression strategy. In Section 5, we used a subset of drops that were directly protecting physical structures to show that, on average, we spent about $85 thousand dollars on LAT drops per home protected. Even though this is not a traditional measure of benefits, it provides a way to evaluate economic tradeoffs in a suppression strategy. The cost-effectiveness metric can be combined with data available to incident managers on economic values on the land where they are developing a suppression campaign, such as the IFTDSS tool (DOI and USDA 2024) to get a sense for the level of potential avoided damages across several resource/asset types.

It is important to note that this tool cannot and will not be a panacea for wildfire suppression strategy due to many of the non-priced components of a retardant drop. For example, our results show that placing drops in trees is much less effective than allocating them to land with more shrub-type fuels. No matter the expected probability of suppression effectiveness for the retardant in a location, the IC may place emphasis on firefighter safety in their decision over cost-effectiveness. If that were the case, they may choose to take a chance on the retardant drop suppressing fire in the trees to avoid putting firefighters at risk, instead of the shrub field where the probability of success is high. Extensive research has shown that wildfire retardant is potentially harmful to the environment (Puglis, Iacchetta, and Mackey 2022; Crouch et al. 2006b), mainly through contaminating watersheds, suggesting there are non-priced costs to a retardant drop as well. Therefore, any proper accounting of the full range of costs and benefits of a potential retardant drop in a suppression campaign needs to weigh these types of non-market considerations.

The cost-effectiveness measure could be used as a decision support tool similar to the value of statistical life (VSL). Economists and epidemiologists use VSL to measure the balance between risk and financial capital (Kniesner and Viscusi 2019). It is used to measure the value of an improvement in health outcomes like life expectancy. Wildfire incident managers could follow a similar practice, using the measure to balance protected values and the probability of containment success.

The cost-effectiveness metric we develop is valuable for the allocation of public goods, where equity and efficiency are important considerations. This approach ensures that decisions are not skewed toward protecting the most affluent areas by abstracting away from purely financial measures. Relying on property values in suppression effort allocations could disproportionately direct firefighting resources toward wealthier communities, possibly leaving vulnerable areas underprotected. This would not align with the broader public interest. The cost-effectiveness metric focuses on maximizing overall public benefit by prioritizing risk reduction and success in resource allocation. A similar cost-effectiveness measure could be developed to guide the allocation of funds for controlling water pollution, advancing renewable energy projects, and managing a wide range of natural resources.

The spatial differences-in-differences model can be used in other research in natural resource economics to determine the effectiveness of a treatment for a natural phenomenon developing over space, as opposed to time. While spatial RDDs are capable of analyzing this effect in certain scenarios, I believe this method has advantages in four distinct scenarios. First, if we have reason to believe that the location of the spatial intervention had something inherently unobservable changing at the cutoff besides the discrete spatial measure of treatment. For example, in this research, that could be the beliefs of a firefighter, incident manager, or pilot. Second, if we theorize that there are non-sharp treatment effects of the intervention. For example, could the wildfire continue to interact with the fire retardant it absorbed as it grows? Third, this estimation strategy may provide a better idea of an overall treatment effect for a protected area when we have reason to believe the spatially evolving process could approach the protected area from more direction than one. Finally, this estimation strategy can minimize the statistical bias introduced into the treatment effectiveness of a spatial intervention with pseudo-random starting and ending locations, given proper data.

For many of the reasons stated above, this estimation strategy has powerful applications for two veins of the natural resource economic literature: evaluation of wildfire fuel treatment effectiveness[81] and invasive species management. Research on the effectiveness of pre-wildfire risk mitigation projects suffers from the same selection issue that surrounds the estimation of suppression resource effectiveness. Typically, the risk or hazard of wildfire is a consideration in the location of fuels treatment project (Ohlson et al. 2006), biasing the analysis of their effectiveness in a naive regression. While there have been several studies that aim to parameterize the effectiveness of such projects that avoid the issue of selection in a robust manner, they either focus on a non-spatial outcome like costs (Sánchez et al. 2019) or focus on a very specific environment (Butry 2009). This estimation strategy could be implemented over a large subset of projects to evaluate how they alter wildfire outcomes.

Invasive species spread is analogous to wildfire as it does not always take a uniform spread pattern and is a function of a wide variety of physical, environmental, and social reasons. This estimation strategy could be used to estimate the effectiveness of a spatial treatment against an invasive species spread. That information could then build upon existing research on the optimal model for spatial control against invasive species spread (Epanchin-Niell and Liebhold 2015; Epanchin-Niell and Wilen 2012). Spatial interventions of invasive species control don't only have sharp treatment effects; it is possible that their extensive margin impact could decay beyond the treatment (Castaño et al. 2023). Additionally, this estimation strategy could be used to evaluate the effectiveness of other spatially evolving phenomena like floods or point source pollution.

Our work can be used to aid governments and land managers in better understanding the full range of costs and benefits of a decision aimed at reducing environmental damages. As climate change escalates, so does the frequency and severity of climate disasters (Bhola et al. 2023). The federal government has identified a crucial need to determine the effectiveness of actions to reduce the damages from these disasters (White House OMB 2023), particularly for wildfires. This gap in knowledge highlights the need for more granular effectiveness estimates, such as those produced in this research, to aid in optimal resource allocation. Once an intervention's effectiveness is

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[81] As opposed to this research on wildfire suppression effectiveness

established, economic benefits can be estimated using a cost-effectiveness metric similar to the one we developed, alongside valuations for the assets protected.

4.7 Conclusion

In this analysis, we seek to parameterize the effectiveness of large airtankers (LATs) at suppressing the growth of wildfire. We build a unique dataset using spatial information on LAT retardant drops and cells of land in and around a wildfire. A spatial difference-in-differences framework is used to find that the land directly behind a LAT drop is 8.4% less likely to burn. Our spatial difference-in-differences estimates show that LATs are also effective at reducing the intensity of the wildfire's burn by 7.6% and delaying the spread by over four hours. RDD estimation is used to find that LAT drops are effective at reducing the extent of a fire's spread by about 21% percentage points and reducing the intensity of the burn by about 18% as it spreads over the retardant.

This research is really important for several different reasons. First, it's crucial to broaden our understanding of the relative strengths and weaknesses of using aviation to fight wildfires. Previous research like the 2020 Aerial Firefighting Use and Effectiveness (U.S. Forest Service 2020) study was important in highlighting ways that aviation was effective in meeting the needs of incident management. This research will be able to supplement that with an objective measure of LATs' ability to suppress the growth of fire. Second, as wildfires grow more hazardous across the country and land managers operate with resource constraints that are binding at a higher rate, it's important to understand the substitutability of different types of wildfire suppression resources. This study provides a formal parameter of aviation's capacity to diminish the growth of fire. That will be crucial information if we want to derive, for example, the elasticity of substitution between air and ground resources on a wildfire.

Third, while we have a robust grasp of the costs associated with wildfire suppression strategies, we have a limited knowledge of their benefits. Estimating the suppression effectiveness of a resource allows us to calculate avoided damages. In turn, that can allow us to estimate a resource deployment's economic benefit. This is especially relevant in a federal policy environment where legislation[82] has been implemented to reduce economic damages from wildfire through increased pre-incident fuels management. Quantifying the benefits of active wildfire suppression strategies will allow us to target better locations for fuel treatment projects.

Finally, we provide a unique model that can be used (given certain data availability) to obtain causal estimates of the effectiveness of a spatially allocated resource that aims to interfere (positively or negatively) in the spatial growth of a phenomenon, such as point-source pollution or the spread of an invasive species. This method will be useful for determining a general treatment effect for a pre-defined area, as opposed to a sharp treatment effect.

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[82] See: Wildfire Crisis Strategy (U.S. Department of Agriculture, Forest Service 2022)

Bibliography

Abatzoglou, John T. (Jan. 2013). “Development of gridded surface meteorological data for ecological applications and modelling”. en. In: *International Journal of Climatology* 33.1, pp. 121–131. ISSN: 08998418. DOI: 10.1002/joc.3413. URL: https://onlinelibrary.wiley.com/doi/10.1002/joc.3413 (visited on 09/25/2023).

Abatzoglou, John T. and Crystal A. Kolden (2011). “Relative importance of weather and climate on wildfire growth in interior Alaska”. en. In: *International Journal of Wildland Fire* 20.4, p. 479. ISSN: 1049-8001. DOI: 10.1071/WF10046. URL: http://www.publish.csiro.au/?paper=WF10046 (visited on 10/05/2023).

Abatzoglou, John T. and A. Park Williams (Oct. 2016). “Impact of anthropogenic climate change on wildfire across western US forests”. en. In: *Proceedings of the National Academy of Sciences* 113.42, pp. 11770–11775. ISSN: 0027-8424, 1091-6490. DOI: 10.1073/pnas.1607171113. URL: https://pnas.org/doi/full/10.1073/pnas.1607171113 (visited on 08/10/2022).

Adams, M.D. and S. Charnley (2018). “Environmental justice and US Forest Service hazardous fuels reduction: A spatial method for impact assessment of federal resource management actions.” In: *Applied Geography* 90, pp. 257–271. DOI: https://doi.org/10.1016/j.apgeog.2017.12.014. URL: https://www.sciencedirect.com/science/article/pii/S0143622817300231?casa_token=bwX8uZWRXa4AAAAA:5RV3eK7nbWZ-QflWze5QJtb-rh9KCOnFbC_yYJWeyPXrta7BFMgyABT SMeIsm-A.

An, Yunbi et al. (June 2022). “Media attention and agency costs: Evidence from listed companies in China”. en. In: *Journal of International Money and Finance* 124, p. 102609. ISSN: 02615606. DOI: 10.1016/j.jimonfin.2022.102609. URL: https://linkinghub.elsevier.com/retrieve/pii/S0261560622000122 (visited on 09/26/2023).

Anderson, Sarah E., Andrew J. Plantinga, and Matthew J. Wibbenmeyer (Aug. 2022). “Inequality in Agency Response: Evidence from Salient Wildfire Events”. en. In: *The Journal of Politics*,

p. 722044. ISSN: 0022-3816, 1468-2508. DOI: 10.1086/722044. URL: https://www.journals.uchicago.edu/doi/10.1086/722044 (visited on 12/29/2022).

Anderson, Sarah E., Andrew J. Plantinga, and Matthew J. Wibbenmeyer (Jan. 2023). "Unequal Treatments: Federal Wildfire Fuels Projects and Socioeconomic Status of Nearby Communities". en. In: *Environmental and Energy Policy and the Economy* 4, pp. 177–201. ISSN: 2689-7857, 2689-7865. DOI: 10.1086/722676. URL: https://www.journals.uchicago.edu/doi/10.1086/722676 (visited on 05/22/2023).

Andersson, Kelly (June 2023). *Airtankers ON*. URL: https://fireaviation.com/2023/06/02/airtankers-on/.

Angrist, Joshua and Guido Imbens (1995). *Identification and estimation of local average treatment effects*.

Archibald, Sally et al. (Apr. 2013). "Defining pyromes and global syndromes of fire regimes". en. In: *Proceedings of the National Academy of Sciences* 110.16, pp. 6442–6447. ISSN: 0027-8424, 1091-6490. DOI: 10.1073/pnas.1211466110. URL: https://pnas.org/doi/full/10.1073/pnas.1211466110 (visited on 03/06/2023).

Baijnath-Rodino, Janine A. et al. (Sept. 2023). "Quantifying the effectiveness of shaded fuel breaks from ground-based, aerial, and spaceborne observations". en. In: *Forest Ecology and Management* 543, p. 121142. ISSN: 03781127. DOI: 10.1016/j.foreco.2023.121142. URL: https://linkinghub.elsevier.com/retrieve/pii/S0378112723003766 (visited on 10/04/2023).

Bakkensen, Laura A. and Lala Ma (Nov. 2020). "Sorting over flood risk and implications for policy reform". en. In: *Journal of Environmental Economics and Management* 104, p. 102362. ISSN: 00950696. DOI: 10.1016/j.jeem.2020.102362. URL: https://linkinghub.elsevier.com/retrieve/pii/S0095069620300851 (visited on 08/10/2022).

Banzhaf, Spencer, Lala Ma, and Christopher Timmins (Feb. 2019). "Environmental Justice: The Economics of Race, Place, and Pollution". en. In: *Journal of Economic Perspectives* 33.1, pp. 185–208. ISSN: 0895-3309. DOI: 10.1257/jep.33.1.185. URL: https://pubs.aeaweb.org/doi/10.1257/jep.33.1.185 (visited on 08/10/2022).

Bayham, Jude, Erin J. Belval, et al. (Feb. 2020). “Weather, Risk, and Resource Orders on Large Wildland Fires in the Western US”. en. In: *Forests* 11.2, p. 169. ISSN: 1999-4907. DOI: 10.3390/f11020169. URL: https://www.mdpi.com/1999-4907/11/2/169 (visited on 12/01/2022).

Bayham, Jude and Jonathan K. Yoder (Feb. 2020). “Resource Allocation under Fire”. en. In: *Land Economics* 96.1, pp. 92–110. ISSN: 0023-7639, 1543-8325. DOI: 10.3368/le.96.1.92. URL: http://le.uwpress.org/lookup/doi/10.3368/le.96.1.92 (visited on 12/01/2022).

Bayham, Jude, Jonathan K. Yoder, et al. (2022). “The economics of wildfire in the United States”. In: *Annual Review of Resource Economics* 14.1, pp. 379–401.

Baylis, Patrick and Judson Boomhower (Dec. 2019). “Moral Hazard, Wildfires, and the Economic Incidence of Natural Disasters”. en. In: w26550, w26550. DOI: 10.3386/w26550. URL: http://www.nber.org/papers/w26550.pdf (visited on 09/26/2023).

— (Jan. 2023). “The Economic Incidence of Wildfire Suppression in the United States”. en. In: *American Economic Journal: Applied Economics* 15.1, pp. 442–473. ISSN: 1945-7782, 1945-7790. DOI: 10.1257/app.20200662. URL: https://pubs.aeaweb.org/doi/10.1257/app.20200662 (visited on 03/31/2024).

Belval, Erin J., Jude Bayham, and Shayne Magstadt (2024). “Retention of highly qualified wildland firefighters in the Western United States”. In: *Forest Policy and Economics* 158, p. 103115.

Belval, Erin J., Karen C. Short, et al. (Mar. 2022). “A Historical Perspective to Inform Strategic Planning for 2020 End-of-Year Wildland Fire Response Efforts”. en. In: *Fire* 5.2, p. 35. ISSN: 2571-6255. DOI: 10.3390/fire5020035. URL: https://www.mdpi.com/2571-6255/5/2/35 (visited on 12/24/2022).

Belval, Erin J., Crystal S. Stonesifer, and David E. Calkin (Feb. 2020a). “Fire Suppression Resource Scarcity: Current Metrics and Future Performance Indicators”. en. In: *Forests* 11.2, p. 217. ISSN: 1999-4907. DOI: 10.3390/f11020217. URL: https://www.mdpi.com/1999-4907/11/2/217 (visited on 04/04/2024).

— (2020b). “Fire suppression resource scarcity: Current metrics and future performance indicators”. In: *Forests* 11.2, p. 217.

Belval, Erin J., Yu Wei, et al. (2017). “Studying interregional wildland fire engine assignments for large fire suppression”. en. In: *International Journal of Wildland Fire* 26.7, p. 642. ISSN: 1049-8001. DOI: 10.1071/WF16162. URL: http://www.publish.csiro.au/?paper=WF16162 (visited on 08/21/2023).

Bhadari, B. et al. (2002). *LandScan: locating people is what matters.*

Bhola, Vijai et al. (2023). “Escalating costs of billion-dollar disasters in the US: climate change necessitates disaster risk reduction”. In: *The Journal of Climate Change and Health* 10, p. 100201.

Brewer, Matthew J. and Craig B. Clements (2019). “The 2018 Camp Fire: Meteorological analysis using in situ observations and numerical simulations”. In: *Atmosphere* 11.1, p. 47.

Buechi, Hanna et al. (2021). “Long-term trends in wildfire damages in California”. In: *International journal of wildland fire* 30.10, pp. 757–762.

Bullard, Robert D. (Apr. 1983). “Solid Waste Sites and the Black Houston Community”. en. In: *Sociological Inquiry* 53.2-3, pp. 273–288. ISSN: 0038-0245, 1475-682X. DOI: 10.1111/j.1475-682X.1983.tb00037.x. URL: https://onlinelibrary.wiley.com/doi/10.1111/j.1475-682X.1983.tb00037.x (visited on 08/10/2022).

Bullard, Robert D. and Beverly Wright, eds. (2009). *Race, place, and environmental justice after Hurricane Katrina: struggles to reclaim, rebuild, and revitalize New Orleans and the Gulf Coast*. OCLC: ocn251196760. Boulder, CO: Westview Press. ISBN: 978-0-8133-4424-9.

Burke, Marshall, Anne Driscoll, et al. (Jan. 2021). “The changing risk and burden of wildfire in the United States”. en. In: *Proceedings of the National Academy of Sciences* 118.2, e2011048118. ISSN: 0027-8424, 1091-6490. DOI: 10.1073/pnas.2011048118. URL: https://pnas.org/doi/full/10.1073/pnas.2011048118 (visited on 08/10/2022).

Burke, Marshall, Sam Heft-Neal, et al. (July 2022). “Exposures and behavioural responses to wildfire smoke”. en. In: *Nature Human Behaviour* 6.10, pp. 1351–1361. ISSN: 2397-3374. DOI: 10.1038/s41562-022-01396-6. URL: https://www.nature.com/articles/s41562-022-01396-6 (visited on 03/31/2024).

Butler, Corey R., Mary B. O'Connor, and Jennifer M. Lincoln (July 2015). "Aviation-Related Wildland Firefighter Fatalities — United States, 2000–2013". In: *MMWR. Morbidity and Mortality Weekly Report* 64.29, pp. 793–796. ISSN: 0149-2195, 1545-861X. DOI: 10.15585/mmwr.mm6429a4. URL: http://www.cdc.gov/mmwr/preview/mmwrhtml/mm6429a4.htm (visited on 11/26/2022).

Butry, David T. (June 2009). "Fighting fire with fire: estimating the efficacy of wildfire mitigation programs using propensity scores". en. In: *Environmental and Ecological Statistics* 16.2, pp. 291–319. ISSN: 1352-8505, 1573-3009. DOI: 10.1007/s10651-007-0083-3. URL: http://link.springer.com/10.1007/s10651-007-0083-3 (visited on 06/03/2024).

Calderón-Argelich, Amalia et al. (Oct. 2021). "Tracing and building up environmental justice considerations in the urban ecosystem service literature: A systematic review". en. In: *Landscape and Urban Planning* 214, p. 104130. ISSN: 01692046. DOI: 10.1016/j.landurbplan.2021.104130. URL: https://linkinghub.elsevier.com/retrieve/pii/S0169204621000931 (visited on 08/16/2024).

Calkin, David E. and Christopher O'Connor (Aug. 2022). "Integrating Pre-Season Planning with Event Response: The PODS—RMA Framework". en. In: *ICFBR 2022*. MDPI, p. 51. DOI: 10.3390/environsciproc2022017051. URL: https://www.mdpi.com/2673-4931/17/1/51 (visited on 01/14/2023).

Calkin, David E., Crystal S. Stonesifer, et al. (2014). "Large airtanker use and outcomes in suppressing wildland fires in the United States". In: *International Journal of Wildland Fire* 23.2, pp. 259–271.

Calkin, David E., Matthew P. Thompson, and Mark A. Finney (Dec. 2015). "Negative consequences of positive feedbacks in US wildfire management". en. In: *Forest Ecosystems* 2.1, p. 9. ISSN: 2197-5620. DOI: 10.1186/s40663-015-0033-8. URL: https://forestecosyst.springeropen.com/articles/10.1186/s40663-015-0033-8 (visited on 09/26/2023).

Carvalho, Camila, Ainhoa González Del Campo, and Diogo De Carvalho Cabral (May 2022). "Scales of inequality: The role of spatial extent in environmental justice analysis". en. In: *Land-*

scape and Urban Planning 221, p. 104369. ISSN: 01692046. DOI: 10.1016/j.landurbplan.2022.104369. URL: https://linkinghub.elsevier.com/retrieve/pii/S0169204622000184 (visited on 08/15/2024).

Castaño, Paula A. et al. (Mar. 2023). "Invasive rodent eradication on islands: assessment and mitigation of human exposure to rodenticides". en. In: *Biological Invasions* 25.3, pp. 653–671. ISSN: 1387-3547, 1573-1464. DOI: 10.1007/s10530-022-02940-1. URL: https://link.springer.com/10.1007/s10530-022-02940-1 (visited on 06/03/2024).

Castellnou, Marc et al. (Dec. 2019). "Empowering strategic decision-making for wildfire management: avoiding the fear trap and creating a resilient landscape". en. In: *Fire Ecology* 15.1, 31, s42408–019–0048–6. ISSN: 1933-9747. DOI: 10.1186/s42408-019-0048-6. URL: https://fireecology.springeropen.com/articles/10.1186/s42408-019-0048-6 (visited on 06/20/2023).

Chakraborty, Jayajit, Timothy W. Collins, and Sara E. Grineski (Feb. 2019). "Exploring the Environmental Justice Implications of Hurricane Harvey Flooding in Greater Houston, Texas". en. In: *American Journal of Public Health* 109.2, pp. 244–250. ISSN: 0090-0036, 1541-0048. DOI: 10.2105/AJPH.2018.304846. URL: https://ajph.aphapublications.org/doi/full/10.2105/AJPH.2018.304846 (visited on 08/10/2022).

Crouch, Robert L. et al. (2006a). "Post-fire surface water quality: Comparison of fire retardant versus wildfire-related effects". In: *Chemosphere* 62.6, pp. 874–889.

— (Feb. 2006b). "Post-fire surface water quality: Comparison of fire retardant versus wildfire-related effects". en. In: *Chemosphere* 62.6, pp. 874–889. ISSN: 00456535. DOI: 10.1016/j.chemosphere.2005.05.031. URL: https://linkinghub.elsevier.com/retrieve/pii/S0045653505007435 (visited on 06/02/2024).

Cuadrado-Ballesteros, Beatriz, José Frías-Aceituno, and Jennifer Martínez-Ferrero (Jan. 2014). "The role of media pressure on the disclosure of sustainability information by local governments". en. In: *Online Information Review* 38.1, pp. 114–135. ISSN: 1468-4527. DOI: 10.1108/OIR-12-2012-0232. URL: https://www.emerald.com/insight/content/doi/10.1108/OIR-12-2012-0232/full/html (visited on 09/28/2023).

Cullen, Alison C., Travis Axe, and Harry Podschwit (2020). “High-severity wildfire potential–associating meteorology, climate, resource demand and wildfire activity with preparedness levels”. In: *International journal of wildland fire* 30.1, pp. 30–41.

D’Evelyn, Savannah M. et al. (May 2022). “Wildfire, Smoke Exposure, Human Health, and Environmental Justice Need to be Integrated into Forest Restoration and Management”. en. In: *Current Environmental Health Reports* 9.3, pp. 366–385. ISSN: 2196-5412. DOI: 10.1007/s40572-022-00355-7. URL: https://link.springer.com/10.1007/s40572-022-00355-7 (visited on 03/31/2024).

Daniels, Molly C. et al. (Feb. 2024). “Multiple social and environmental factors affect wildland fire response of full or less-than-full suppression”. en. In: *Journal of Environmental Management* 351, p. 119731. ISSN: 03014797. DOI: 10.1016/j.jenvman.2023.119731. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301479723025197 (visited on 04/04/2024).

Dennison, Philip E. et al. (Apr. 2014). “Large wildfire trends in the western United States, 1984-2011”. en. In: *Geophysical Research Letters* 41.8, pp. 2928–2933. ISSN: 00948276. DOI: 10.1002/2014GL059576. URL: http://doi.wiley.com/10.1002/2014GL059576 (visited on 08/10/2022).

Depro, Brooks, Christopher Timmins, and Maggie O’Neil (Sept. 2015). “White Flight and Coming to the Nuisance: Can Residential Mobility Explain Environmental Injustice?” en. In: *Journal of the Association of Environmental and Resource Economists* 2.3, pp. 439–468. ISSN: 2333-5955, 2333-5963. DOI: 10.1086/682716. URL: https://www.journals.uchicago.edu/doi/10.1086/682716 (visited on 12/29/2022).

Dillon, Greg and Juliet Gibertson-Day (2020). “Wildfire Hazard Potential for the United States (270-m), version 2020”. In: *USFS*.

DOI and USDA (2024). *Interagency Fuel Treatment Decision Support System (IFTDSS)*. URL: https://iftdss.firenet.gov/firenetHelp/help/pageHelp/content/00-aboutiftdss/disclaimer.htm.

Donovan, Geoffrey H., Jeffrey P. Prestemon, and Krista Gebert (Aug. 2011). “The Effect of Newspaper Coverage and Political Pressure on Wildfire Suppression Costs”. en. In: *Society & Natu-*

ral Resources 24.8, pp. 785–798. ISSN: 0894-1920, 1521-0723. URL: http://www.tandfonline.com/doi/abs/10.1080/08941921003649482 (visited on 12/01/2022).

Donovan, Geoffrey H. and Douglas B. Rideout (2003). “A reformulation of the cost plus net value change (C+ NVC) model of wildfire economics”. In: *Forest Science* 49.2, pp. 318–323.

Dowle, M. et al. (2021). *exactextractr: Fast Extraction of Exact Raster Values from Polygons*. R package version 1.2.1. URL: https://CRAN.R-project.org/package=exactextractr.

Dubay, Steve E. (2015). “Improving access to military aircraft during civilian wildfires”. PhD thesis. Monterey, California: Naval Postgraduate School.

Duff, Thomas J. and Kevin G. Tolhurst (2015). “Operational wildfire suppression modelling: a review evaluating development, state of the art and future directions”. In: *International Journal of Wildland Fire* 24.6, pp. 735–748.

EPA (2022). “EJScreen: Environmental Justice Screening and Mapping Tool”. In: *Environmental Protection Agency*.

Epanchin-Niell, Rebecca S. and Andrew M. Liebhold (Aug. 2015). “Benefits of invasion prevention: Effect of time lags, spread rates, and damage persistence”. en. In: *Ecological Economics* 116, pp. 146–153. ISSN: 09218009. DOI: 10.1016/j.ecolecon.2015.04.014. URL: https://linkinghub.elsevier.com/retrieve/pii/S092180091500172X (visited on 06/03/2024).

Epanchin-Niell, Rebecca S. and James E. Wilen (Mar. 2012). “Optimal spatial control of biological invasions”. en. In: *Journal of Environmental Economics and Management* 63.2, pp. 260–270. ISSN: 00950696. DOI: 10.1016/j.jeem.2011.10.003. URL: https://linkinghub.elsevier.com/retrieve/pii/S0095069611001392 (visited on 06/03/2024).

Finney, Mark A. et al. (2011). “A simulation of probabilistic wildfire risk components for the continental United States”. In: *Stochastic Environmental Research and Risk Assessment* 25, pp. 973–1000.

Forest Service, U.S. (2020). “Rocky Mountain Coordinating Group 2020 MAC Plan”. In: URL: https://gacc.nifc.gov/rmcc/administrative/rmcg/RMA_MAC_Plan.pdf.

Forest Service, U.S., California Dept of Forestry and Fire Protection, et al. (2022). *California Interagency Mobilization Guide*. URL: https://gacc.nifc.gov/oscc/mobguide/2022/2022Full.pdf.

Forest Service, U.S. and Bureau of Land Management (2020). *13 Anderson Fire Behavior Fuel Models*. URL: https://www.landfire.gov/fbfm13.php.

Gannon, Benjamin M., Matthew P. Thompson, et al. (Aug. 2020). "A Geospatial Framework to Assess Fireline Effectiveness for Large Wildfires in the Western USA". en. In: *Fire* 3.3, p. 43. ISSN: 2571-6255. DOI: 10.3390/fire3030043. URL: https://www.mdpi.com/2571-6255/3/3/43 (visited on 10/03/2023).

Gannon, Benjamin M., Yu Wei, et al. (2023). "A quantitative analysis of fuel break effectiveness drivers in Southern California National Forests". In: *Fire* 6.3, p. 104.

Gergely, K.J. and A. McKerrow (2016). *PAD-US—National inventory of protected areas (ver. 1.2, December 2020)*. URL: https://pubs.usgs.gov/fs/2013/3086/.

Gesch, D. et al. (2009). *National Map - Elevation*. URL: https://pubs.usgs.gov/fs/2009/3053/.

Haas, Jessica R., David E. Calkin, and Matthew P. Thompson (Feb. 2015). "Wildfire Risk Transmission in the Colorado Front Range, USA: Wildfire Risk Transmission". en. In: *Risk Analysis* 35.2, pp. 226–240. ISSN: 02724332. DOI: 10.1111/risa.12270. URL: https://onlinelibrary.wiley.com/doi/10.1111/risa.12270 (visited on 12/10/2022).

Hahn, Jinyong, Petra Todd, and Wilbert Van der Klaauw (2001). "Identification and estimation of treatment effects with a regression-discontinuity design". In: *Econometrica* 69.1, pp. 201–209.

Hand, Michael S., Krista M. Gebert, et al. (2014). "Introduction: A New Look at Wildfire Management Expenditures". en. In: *Economics of Wildfire Management*. Series Title: SpringerBriefs in Fire. New York, NY: Springer New York, pp. 1–4. ISBN: 978-1-4939-0577-5 978-1-4939-0578-2. DOI: 10.1007/978-1-4939-0578-2_1. URL: https://link.springer.com/10.1007/978-1-4939-0578-2_1 (visited on 09/26/2023).

Hand, Michael S., Hari Katuwal, et al. (2017). "The influence of incident management teams on the deployment of wildfire suppression resources". en. In: *International Journal of Wildland*

Fire 26.7, p. 615. ISSN: 1049-8001. DOI: 10.1071/WF16126. URL: http://www.publish.csiro.au/?paper=WF16126 (visited on 12/01/2022).

Hand, Michael S., Matthew J. Wibbenmeyer, et al. (Oct. 2015). "Risk Preferences, Probability Weighting, and Strategy Tradeoffs in Wildfire Management: Risk Preferences, Probability Weighting". en. In: *Risk Analysis* 35.10, pp. 1876–1891. ISSN: 02724332. DOI: 10.1111/risa.12457. URL: https://onlinelibrary.wiley.com/doi/10.1111/risa.12457 (visited on 09/26/2023).

Har, Janie and Felicia Fonseca (2020). "Media access to wildfires, disasters varies widely by state". In: *AP News*. URL: https://apnews.com/article/wildfires-media-oregon-washington-redskins-forestry-4c7f60408e3841540b4172a2e6b95e25.

Harrison, Jill L. (2011). *Pesticide drift and the pursuit of environmental justice*. English. OCLC: 767669353. Cambridge, Mass.: MIT Press. ISBN: 9780262298766. URL: http://site.ebrary.com/id/10517482 (visited on 08/10/2022).

Hawbaker, Todd J. et al. (July 2005). "Road Density and Landscape Pattern in Relation to Housing Density, and Ownership, Land Cover, and Soils". en. In: *Landscape Ecology* 20.5, pp. 609–625. ISSN: 0921-2973, 1572-9761. DOI: 10.1007/s10980-004-5647-0. URL: http://link.springer.com/10.1007/s10980-004-5647-0 (visited on 12/09/2022).

Heckman, James J. (1996). "Identification of causal effects using instrumental variables: Comment". In: *Journal of the American Statistical Association* 91.434, pp. 459–462.

Hijmans, A. (2021). *terra: Spatial Data Analysis with Terry Anderson*. R package version 1.4-29. URL: https://CRAN.R-project.org/package=terra.

Hijmans, R. J. (2021). *raster: Geographic Data Analysis and Modeling*. R package version 3.5-17. URL: https://CRAN.R-project.org/package=raster.

Hoffman, Robert L. and Goli Davidson (2003). "Equitable Allocation of Limited Resources". In.

Holden, Zachary A. and W. Matt Jolly (Dec. 2011). "Modeling topographic influences on fuel moisture and fire danger in complex terrain to improve wildland fire management decision support". en. In: *Forest Ecology and Management* 262.12, pp. 2133–2141. ISSN: 03781127.

DOI: 10.1016/j.foreco.2011.08.002. URL: https://linkinghub.elsevier.com/retrieve/pii/S0378112711004774 (visited on 10/05/2023).

Holmes, Thomas P. and David E. Calkin (2013). “Econometric analysis of fire suppression production functions for large wildland fires”. en. In: *International Journal of Wildland Fire* 22.2, p. 246. ISSN: 1049-8001. DOI: 10.1071/WF11098. URL: http://www.publish.csiro.au/?paper=WF11098 (visited on 04/04/2024).

Hoover, Edgar M. (1936). “The measurement of industrial localization”. In: *The Review of Economic Statistics*, pp. 162–171.

IMSR (2023). “Incident Management Situation Report (IMSR)”. In: *National Interagency Coordination Center*. URL: https://www.nifc.gov/nicc/incident-information/imsr.

Jetter, Michael (2014). “Terrorism and the Media”. en. In: *SSRN Electronic Journal*. ISSN: 1556-5068. DOI: 10.2139/ssrn.2505359. URL: https://www.ssrn.com/abstract=2505359 (visited on 09/26/2023).

Johnson Gaither, Cassandra et al. (Aug. 2019). “African American Exposure to Prescribed Fire Smoke in Georgia, USA”. en. In: *International Journal of Environmental Research and Public Health* 16.17, p. 3079. ISSN: 1660-4601. DOI: 10.3390/ijerph16173079. URL: https://www.mdpi.com/1660-4601/16/17/3079 (visited on 08/09/2022).

Jones, Benjamin A. and Robert P. Berrens (Apr. 2021). “PRESCRIBED BURNS, SMOKE EXPOSURE, AND INFANT HEALTH”. en. In: *Contemporary Economic Policy* 39.2, pp. 292–309. ISSN: 1074-3529, 1465-7287. DOI: 10.1111/coep.12509. URL: https://onlinelibrary.wiley.com/doi/10.1111/coep.12509 (visited on 08/22/2022).

Kalabokidis, Kostas D. (2000). “Effects of wildfire suppression chemicals on people and the environment—a review”. In: *Global Nest: The International Journal* 2.2, pp. 129–137.

Katuwal, Hari, David E. Calkin, and Michael S. Hand (2016a). “Production and efficiency of large wildland fire suppression effort: A stochastic frontier analysis”. In: *Journal of environmental management* 166, pp. 227–236.

Katuwal, Hari, David E. Calkin, and Michael S. Hand (Jan. 2016b). "Production and efficiency of large wildland fire suppression effort: A stochastic frontier analysis". en. In: *Journal of Environmental Management* 166, pp. 227–236. ISSN: 03014797. DOI: 10.1016/j.jenvman.2015.10.030. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301479715303285 (visited on 04/04/2024).

Kelly, Erin Clover, Susan Charnley, and Jodie T. Pixley (2019). "Polycentric systems for wildfire governance in the Western United States". In: *Land use policy* 89, p. 104214.

Kniesner, Thomas J. and W. Kip Viscusi (2019). "The value of a statistical life". In: *Forthcoming, Oxford Research Encyclopedia of Economics and Finance, Vanderbilt Law Research Paper* 19-15.

Koning, Miriam, Gerard Mertens, and Peter Roosenboom (2010). "The impact of media attention on the use of alternative earnings measures". In: *Abacus* 46.3, pp. 258–288.

Labrecque, Jeremy and Sonja A. Swanson (Sept. 2018). "Understanding the Assumptions Underlying Instrumental Variable Analyses: a Brief Review of Falsification Strategies and Related Tools". en. In: *Current Epidemiology Reports* 5.3, pp. 214–220. ISSN: 2196-2995. DOI: 10.1007/s40471-018-0152-1. URL: http://link.springer.com/10.1007/s40471-018-0152-1 (visited on 09/24/2023).

Larsen, Vegard Høghaug and Leif Anders Thorsrud (2022). "Asset returns, news topics, and media effects". In: *The Scandinavian Journal of Economics* 124.3, pp. 838–868.

Lathwal, Priyank, Parth Vaishnav, and M. Granger Morgan (2022). "Environmental injustice in America: Racial disparities in exposure to air pollution health damages from freight trucking". In: Publisher: arXiv Version Number: 2. DOI: 10.48550/ARXIV.2204.06588. URL: https://arxiv.org/abs/2204.06588 (visited on 11/19/2022).

Leclerc, Philip D., Laura A. McLay, and Maria E. Mayorga (2012). "Modeling Equity for Allocating Public Resources". en. In: *Community-Based Operations Research*. Ed. by Michael P. Johnson. Vol. 167. Series Title: International Series in Operations Research & Management Science. New York, NY: Springer New York, pp. 97–118. ISBN: 978-1-4614-0805-5 978-1-4614-0806-

2. DOI: 10.1007/978-1-4614-0806-2_4. URL: https://link.springer.com/10.1007/978-1-4614-0806-2_4 (visited on 08/16/2024).

Leetaru, Kalev and Philip A. Schrodt (2013). "Gdelt: Global data on events, location, and tone, 1979–2012". In: *ISA annual convention*. Vol. 2. 4. Citeseer, pp. 1–49.

Lepeule, Johanna et al. (2012). "Chronic Exposure to Fine Particles and Mortality: An Extended Follow-up of the Harvard Six Cities Study from 1974 to 2009". In: *Environmental Health Perspectives* 120.7, p. 965.

Li, Guo (Nov. 2023). "Sustainable ecosystem management based on optimal water allocation and equity measures". en. In: *Water Supply* 23.11, pp. 4479–4488. ISSN: 1606-9749, 1607-0798. DOI: 10.2166/ws.2023.276. URL: https://iwaponline.com/ws/article/23/11/4479/98253/Sustainable-ecosystem-management-based-on-optimal (visited on 08/16/2024).

Lin, C.-T Jordan and J. Walter Milon (Aug. 1993). "Attribute and Safety Perceptions in a Double-Hurdle Model of Shellfish Consumption". en. In: *American Journal of Agricultural Economics* 75.3, pp. 724–729. ISSN: 0002-9092, 1467-8276. DOI: 10.2307/1243579. URL: https://onlinelibrary.wiley.com/doi/abs/10.2307/1243579 (visited on 11/01/2022).

Liu, Jia C. et al. (2015). "A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke". In: *Environmental research* 136, pp. 120–132.

Mahrt, Larry (Jan. 2011). "Surface Wind Direction Variability". en. In: *Journal of Applied Meteorology and Climatology* 50.1, pp. 144–152. ISSN: 1558-8432, 1558-8424. DOI: 10.1175/2010JAMC2560.1. URL: http://journals.ametsoc.org/doi/10.1175/2010JAMC2560.1 (visited on 06/20/2023).

Martuzzi, M., F. Mitis, and F. Forastiere (Feb. 2010). "Inequalities, inequities, environmental justice in waste management and health". en. In: *The European Journal of Public Health* 20.1, pp. 21–26. ISSN: 1101-1262, 1464-360X. DOI: 10.1093/eurpub/ckp216. URL: https://academic.oup.com/eurpub/article-lookup/doi/10.1093/eurpub/ckp216 (visited on 08/10/2022).

Marvell, Thomas B. (2019). "Indirect simultaneity". In: *Criminology & Pub. Pol'y* 18, p. 201.

Masri, Shahir, Alana M. W. LeBrón, et al. (2021). "Risk assessment of soil heavy metal contamination at the census tract level in the city of Santa Ana, CA: implications for health and environmental justice". en. In: *Environmental Science: Processes & Impacts* 23.6, pp. 812–830. ISSN: 2050-7887, 2050-7895. DOI: 10.1039/D1EM00007A. URL: http://xlink.rsc.org/?DOI=D1EM00007A (visited on 11/19/2022).

Masri, Shahir, Erica Scaduto, et al. (Apr. 2021). "Disproportionate Impacts of Wildfires among Elderly and Low-Income Communities in California from 2000–2020". en. In: *International Journal of Environmental Research and Public Health* 18.8, p. 3921. ISSN: 1660-4601. DOI: 10.3390/ijerph18083921. URL: https://www.mdpi.com/1660-4601/18/8/3921 (visited on 08/09/2022).

McGinnis, Seth et al. (Aug. 2023). "Future regional increases in simultaneous large Western USA wildfires". en. In: *International Journal of Wildland Fire* 32.9, pp. 1304–1314. ISSN: 1049-8001, 1448-5516. DOI: 10.1071/WF22107. URL: https://www.publish.csiro.au/WF/WF22107 (visited on 03/27/2024).

Milne, Mary et al. (2014). "Evaluating benefits and costs of wildland fires: critical review and future applications". In: *Environmental Hazards* 13.2, pp. 114–132.

Mindock, Clark (May 2023). *Wildfire retardant violates US water law, judge says*. Reuters. URL: https://www.reuters.com/legal/government/wildfire-retardant-violates-us-water-law-judge-says-2023-05-26/ (visited on 08/19/2024).

Miranda, Marie Lynn et al. (May 2011). "Making the Environmental Justice Grade: The Relative Burden of Air Pollution Exposure in the United States". en. In: *International Journal of Environmental Research and Public Health* 8.6, pp. 1755–1771. ISSN: 1660-4601. DOI: 10.3390/ijerph8061755. URL: http://www.mdpi.com/1660-4601/8/6/1755 (visited on 08/10/2022).

Morse, Reilly (2008). *ENVIRONMENTAL JUSTICE THROUGH THE EYE OF HURRICANE KATRINA*. JOINT CENTER FOR POLITICAL and ECONOMIC STUDIES HEALTH POLICY INSTITUTE.

Moseley, Cassandra, Gerardo Sandoval, and Emily J. Davis (2014). “Comparing conditions of labor-intensive forestry and fire suppression workers”. In: *Society & Natural Resources* 27.5, pp. 540–556.

Mullen, Casey et al. (Apr. 2022). “Exploring the distributional environmental justice implications of an air quality monitoring network in Los Angeles County”. en. In: *Environmental Research* 206, p. 112612. ISSN: 00139351. DOI: 10.1016/j.envres.2021.112612. URL: https://linkinghub.elsevier.com/retrieve/pii/S0013935121019137 (visited on 11/19/2022).

Mulligan, Gordon F (1991). “Equality measures and facility location”. In: *Papers in Regional Science* 70.4, pp. 345–365.

Neelon, Brian, Pulak Ghosh, and Patrick F. Loebs (Feb. 2013). “A spatial Poisson hurdle model for exploring geographic variation in emergency department visits: *Spatial Hurdle Model for Exploring Geographic Variation*”. en. In: *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 176.2, pp. 389–413. ISSN: 09641998. DOI: 10.1111/j.1467-985X.2012.01039.x. URL: https://onlinelibrary.wiley.com/doi/10.1111/j.1467-985X.2012.01039.x (visited on 11/01/2022).

Nguyen, Viet Cuong (Mar. 2012). “Program impact evaluation using a matching method with panel data”. en. In: *Statistics in Medicine* 31.6, pp. 577–588. ISSN: 02776715. DOI: 10.1002/sim.4438. URL: https://onlinelibrary.wiley.com/doi/10.1002/sim.4438 (visited on 09/30/2023).

NIFC (2019). *Interagency standards for fire and fire aviation operations*.

— (2023). *Federal Firefighting Costs (Suppression Only)*. Tech. rep. URL: https://www.nifc.gov/fire-information/statistics/suppression-costs (visited on 08/20/2023).

NWCG (Aug. 2023). *First Airtanker Drop (California) – August 12, 1955*. Tech. rep. National Wildfire Coordinating Group. URL: https://www.nwcg.gov/committee/6mfs/first-airtanker-drop#:~:text=The%20first%20operational%20airtanker%20was,tank%20at%20the%20Willows%20airport. (visited on 03/31/2024).

Ohlson, Dan W. et al. (Nov. 2006). “Multi-attribute evaluation of landscape-level fuel management to reduce wildfire risk”. en. In: *Forest Policy and Economics* 8.8, pp. 824–837. ISSN: 13899341.

DOI: 10.1016/j.forpol.2005.01.001. URL: https://linkinghub.elsevier.com/retrieve/pii/S1389934105000286 (visited on 06/02/2024).

Olea, José Luis Montiel and Carolin Pflueger (2013). “A robust test for weak instruments”. In: *Journal of Business & Economic Statistics* 31.3, pp. 358–369.

Olmstead, Sheila, Carolyn Kousky, and Roger Sedjo (2012). “Wildland Fire Suppression and Land Development in the Wildland/Urban Interface”. In: *JFSP Research Project Reports*.

OpenAI (2024). *ChatGPT (October 2024 version)*. https://chat.openai.com/. Large language model.

Pan, Feng, Zexin Diao, and Lin Wang (Apr. 2023). “The impact analysis of media attention on local environmental governance based on four-party evolutionary game”. en. In: *Ecological Modelling* 478, p. 110293. ISSN: 03043800. DOI: 10.1016/j.ecolmodel.2023.110293. URL: https://linkinghub.elsevier.com/retrieve/pii/S0304380023000212 (visited on 09/28/2023).

Parks, Sean A. (2014). “Mapping day-of-burning with coarse-resolution satellite fire-detection data”. en. In: *International Journal of Wildland Fire* 23.2, p. 215. ISSN: 1049-8001. DOI: 10.1071/WF13138. URL: http://www.publish.csiro.au/?paper=WF13138 (visited on 10/01/2023).

Pennick McIver, Chelsea, Philip S. Cook, and Dennis R. Becker (Dec. 2021). “The Fiscal Burden of Wildfires: State Expenditures and Funding Mechanisms for Wildfire Suppression in the Western U.S. and Implications for Federal Policy”. en. In: *State and Local Government Review* 53.4, pp. 337–351. ISSN: 0160-323X, 1943-3409. DOI: 10.1177/0160323X211061353. URL: http://journals.sagepub.com/doi/10.1177/0160323X211061353 (visited on 10/05/2023).

Pereira, Paulo et al. (Aug. 2021). “Short-term effect of wildfires and prescribed fires on ecosystem services”. en. In: *Current Opinion in Environmental Science & Health* 22, p. 100266. ISSN: 24685844. DOI: 10.1016/j.coesh.2021.100266. URL: https://linkinghub.elsevier.com/retrieve/pii/S2468584421000386 (visited on 03/31/2024).

Philippas, Dionisis et al. (Sept. 2019). “Media attention and Bitcoin prices”. en. In: *Finance Research Letters* 30, pp. 37–43. ISSN: 15446123. DOI: 10.1016/j.frl.2019.03.031. URL: https://linkinghub.elsevier.com/retrieve/pii/S1544612319300558 (visited on 09/26/2023).

Plucinski, Matt P. (2012). “Factors affecting containment area and time of Australian forest fires featuring aerial suppression”. In: *Forest Science* 58.4, pp. 390–398.

— (Mar. 2019). “Fighting Flames and Forging Firelines: Wildfire Suppression Effectiveness at the Fire Edge”. en. In: *Current Forestry Reports* 5.1, pp. 1–19. ISSN: 2198-6436. DOI: 10.1007/s40725-019-00084-5. URL: http://link.springer.com/10.1007/s40725-019-00084-5 (visited on 10/05/2023).

Puglis, Holly J., Michael Iacchetta, and Christina M. Mackey (July 2022). “Toxicity of Wildland Fire-Fighting Chemicals in Pulsed Exposures to Rainbow Trout and Fathead Minnows”. en. In: *Environmental Toxicology and Chemistry* 41.7, pp. 1711–1720. ISSN: 0730-7268, 1552-8618. DOI: 10.1002/etc.5347. URL: https://setac.onlinelibrary.wiley.com/doi/10.1002/etc.5347 (visited on 06/02/2024).

R Core Team (2022). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing. Vienna, Austria. URL: https://www.R-project.org/.

Radeloff, Volker C., David P. Helmers, H. Anu Kramer, Miranda H. Mockrin, Patricia M. Alexandre, Avi Bar-Massada, Van Butsic, Todd J. Hawbaker, Sebastián Martinuzzi, Alexandra D. Syphard, et al. (2018). “Rapid growth of the US wildland-urban interface raises wildfire risk”. In: *Proceedings of the National Academy of Sciences* 115.13, pp. 3314–3319.

Radeloff, Volker C., David P. Helmers, H. Anu Kramer, Miranda H. Mockrin, Patricia M. Alexandre, Avi Bar-Massada, Van Butsic, Todd J. Hawbaker, Sebastián Martinuzzi, Alexandra D. Syphard, and Susan I. Stewart (Mar. 2018). “Rapid growth of the US wildland-urban interface raises wildfire risk”. en. In: *Proceedings of the National Academy of Sciences* 115.13, pp. 3314–3319. ISSN: 0027-8424, 1091-6490. DOI: 10.1073/pnas.1718850115. URL: https://pnas.org/doi/full/10.1073/pnas.1718850115 (visited on 03/31/2024).

Restas, Agoston (2023). “Examining the effectiveness of aerial firefighting with the components of firebreak requirements and footprint geometry—Critics of the present practice”. In: *Fire* 6.9, p. 351.

Restás, Ágoston (2014). “Common analysis of the costs and effectiveness of extinguishing materials and aerial firefighting”. In.

Ricker-Gilbert, Jacob, Thomas S. Jayne, and Ephraim Chirwa (Jan. 2011). “Subsidies and Crowding Out: A Double-Hurdle Model of Fertilizer Demand in Malawi”. en. In: *American Journal of Agricultural Economics* 93.1, pp. 26–42. ISSN: 0002-9092, 1467-8276. DOI: 10.1093/ajae/aaq122. URL: https://onlinelibrary.wiley.com/doi/abs/10.1093/ajae/aaq122 (visited on 11/01/2022).

Robinne, François-Nicolas et al. (Feb. 2020). “Wildfire impacts on hydrologic ecosystem services in North American high-latitude forests: A scoping review”. en. In: *Journal of Hydrology* 581, p. 124360. ISSN: 00221694. DOI: 10.1016/j.jhydrol.2019.124360. URL: https://linkinghub.elsevier.com/retrieve/pii/S0022169419310959 (visited on 03/31/2024).

Rossi, David and Olli-Pekka Kuusela (2019). “Cost plus net value change (C+ NVC) revisited: A sequential formulation of the wildfire economics model”. In: *Forest Science* 65.2, pp. 125–136.

Rossi, David, Olli-Pekka Kuusela, and Christopher Dunn (Oct. 2022). “A microeconometric analysis of wildfire suppression decisions in the Western United States”. en. In: *Ecological Economics* 200, p. 107525. ISSN: 09218009. DOI: 10.1016/j.ecolecon.2022.107525. URL: https://linkinghub.elsevier.com/retrieve/pii/S0921800922001872 (visited on 02/07/2023).

Salam, Muhammad T., Talat Islam, and Frank D. Gilliland (Jan. 2008). “Recent evidence for adverse effects of residential proximity to traffic sources on asthma:” en. In: *Current Opinion in Pulmonary Medicine* 14.1, pp. 3–8. ISSN: 1070-5287. DOI: 10.1097/MCP.0b013e3282f1987a. URL: http://journals.lww.com/00063198-200801000-00003 (visited on 12/09/2022).

Sánchez, José J. et al. (June 2019). “Do Fuel Treatments in U.S. National Forests Reduce Wildfire Suppression Costs and Property Damage?” en. In: *Journal of Natural Resources Policy Research* 9.1, pp. 42–73. ISSN: 1939-0459, 1939-0467. DOI: 10.5325/naturesopolirese.9.1.0042. URL: https://scholarlypublishingcollective.org/jnrpr/article/9/1/42/200384/Do-Fuel-Treatments-in-U-S-National-Forests-Reduce (visited on 06/02/2024).

Savas, E.S. (1969). “Simulation and cost-effectiveness analysis of New York’s emergency ambulance service”. In: *Management science* 15.12, B–608.

— (1978). “On equity in providing public services”. In: *Management Science* 8, pp. 800–808.

Schlosberg, David (Feb. 2013). “Theorising environmental justice: the expanding sphere of a discourse”. en. In: *Environmental Politics* 22.1, pp. 37–55. ISSN: 0964-4016, 1743-8934. DOI: 10.1080/09644016.2013.755387. URL: http://www.tandfonline.com/doi/abs/10.1080/09644016.2013.755387 (visited on 08/16/2024).

Short, Karen et al. (2016). “Spatial dataset of probabilistic wildfire risk components for the conterminous United States”. In: *USFS*.

Simard (1976). “Wildland fire management: the economics of policy alternatives.” In.

Simpson, Heather et al. (2022). “Investigating the suitability of aviation tracking data for use in bushfire suppression effectiveness research”. In: *Bushfire Natural Hazards CRC* 2019-2020.

Sinclair, Betsy, Margaret McConnell, and Donald P. Green (2012). “Detecting spillover effects: Design and analysis of multilevel experiments”. In: *American Journal of Political Science* 56.4, pp. 1055–1069.

Smith, Michael D. and Tadesse Wodajo (June 2022). “New Perspectives on Climate Equity and Environmental Justice”. In: *Bulletin of the American Meteorological Society* 103.6, E1522–E1530. ISSN: 0003-0007, 1520-0477. DOI: 10.1175/BAMS-D-22-0032.1. URL: https://journals.ametsoc.org/view/journals/bams/103/6/BAMS-D-22-0032.1.xml (visited on 11/19/2022).

St. Denis, Lise A et al. (2023). “All-hazards dataset mined from the US National Incident Management System 1999–2020”. In: *Scientific data* 10.1, p. 112.

Stetler, Kyle M., Tyron J. Venn, and David E. Calkin (Sept. 2010). “The effects of wildfire and environmental amenities on property values in northwest Montana, USA”. en. In: *Ecological Economics* 69.11, pp. 2233–2243. ISSN: 09218009. DOI: 10.1016/j.ecolecon.2010.06.009. URL: https://linkinghub.elsevier.com/retrieve/pii/S092180091000234X (visited on 08/10/2022).

Stock, James and Motohiro Yogo (2005). “Asymptotic distributions of instrumental variables statistics with many instruments”. In: *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg* 6, pp. 109–120.

Stonesifer, Crystal S., David E. Calkin, Matthew P. Thompson, and Erin J. Belval (Aug. 2021). “Is This Flight Necessary? The Aviation Use Summary (AUS): A Framework for Strategic, Risk-Informed Aviation Decision Support”. en. In: *Forests* 12.8, p. 1078. ISSN: 1999-4907. DOI: 10.3390/f12081078. URL: https://www.mdpi.com/1999-4907/12/8/1078 (visited on 08/22/2022).

Stonesifer, Crystal S., David E. Calkin, Matthew P. Thompson, and Jeffrey D. Kaiden (2014). “Developing an aviation exposure index to inform risk-based fire management decisions”. In: *Journal of Forestry* 112.6, pp. 581–590.

Stonesifer, Crystal S., David E. Calkin, Matthew P. Thompson, and Keith D. Stockmann (2016). “Fighting fire in the heat of the day: an analysis of operational and environmental conditions of use for large airtankers in United States fire suppression”. en. In: *International Journal of Wildland Fire* 25.5, p. 520. ISSN: 1049-8001. DOI: 10.1071/WF15149. URL: http://www.publish.csiro.au/?paper=WF15149 (visited on 12/08/2022).

Storey, Michael Anthony et al. (Jan. 2021). “Experiments on the influence of spot fire and topography interaction on fire rate of spread”. en. In: *PLOS ONE* 16.1. Ed. by Min Huang, e0245132. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0245132. URL: https://dx.plos.org/10.1371/journal.pone.0245132 (visited on 12/09/2022).

Swanson, Sonja A., Jeremy Labrecque, and Miguel A. Hernán (Aug. 2018). “Causal null hypotheses of sustained treatment strategies: What can be tested with an instrumental variable?” en. In: *European Journal of Epidemiology* 33.8, pp. 723–728. ISSN: 0393-2990, 1573-7284. DOI: 10.1007/s10654-018-0396-6. URL: http://link.springer.com/10.1007/s10654-018-0396-6 (visited on 08/28/2024).

Thompson, Matthew P. (June 2014). “Social, Institutional, and Psychological Factors Affecting Wildfire Incident Decision Making”. en. In: *Society & Natural Resources* 27.6, pp. 636–644.

ISSN: 0894-1920, 1521-0723. DOI: 10.1080/08941920.2014.901460. URL: http://www.tandfonline.com/doi/abs/10.1080/08941920.2014.901460 (visited on 09/26/2023).

Thompson, Matthew P., Erin J. Belval, et al. (2023). “Wildfire response: a system on the brink?” In: *Journal of Forestry* 121.2, pp. 121–124.

Thompson, Matthew P., David E. Calkin, Mark A. Finney, et al. (2011). “Integrated national-scale assessment of wildfire risk to human and ecological values”. In.

Thompson, Matthew P., David E. Calkin, Jason Herynk, et al. (2012). “Airtankers and wildfire management in the US Forest Service: examining data availability and exploring usage and cost trends”. In: *International Journal of Wildland Fire* 22.2, pp. 223–233.

— (2013). “Airtankers and wildfire management in the US Forest Service: examining data availability and exploring usage and cost trends”. en. In: *International Journal of Wildland Fire* 22.2, p. 223. ISSN: 1049-8001. DOI: 10.1071/WF11041. URL: http://www.publish.csiro.au/?paper=WF11041 (visited on 09/26/2023).

Thompson, Matthew P., Benjamin M. Gannon, and Michael D. Caggiano (Jan. 2021). “Forest Roads and Operational Wildfire Response Planning”. en. In: *Forests* 12.2, p. 110. ISSN: 1999-4907. DOI: 10.3390/f12020110. URL: https://www.mdpi.com/1999-4907/12/2/110 (visited on 11/10/2022).

Thompson, Matthew P., Benjamin M. Gannon, Michael D. Caggiano, et al. (Aug. 2020). “Prototyping a Geospatial Atlas for Wildfire Planning and Management”. en. In: *Forests* 11.9, p. 909. ISSN: 1999-4907. DOI: 10.3390/f11090909. URL: https://www.mdpi.com/1999-4907/11/9/909 (visited on 06/02/2024).

Thompson, Matthew P., Christopher D. O’Connor, et al. (2022). “Potential operational delineations: new horizons for proactive, risk-informed strategic land and fire management”. In: *Fire Ecology* 18.1, p. 17.

Trouet, Valerie et al. (Feb. 2010). “Fire-climate interactions in the American West since 1400 CE: FIRE-CLIMATE INTERACTIONS”. en. In: *Geophysical Research Letters* 37.4. ISSN:

00948276. DOI: 10.1029/2009GL041695. URL: http://doi.wiley.com/10.1029/2009GL041695 (visited on 08/22/2022).

U.S. Department of Agriculture, Forest Service (2022). *Wildfire Crisis Strategy Implementation Plan*. FS–1187b. URL: https://www.fs.usda.gov.

U.S. Forest Service (2020). *Assessment of Fire Use Effects on Air Quality and Visibility - Final Report*. Tech. rep. U.S. Department of Agriculture, Forest Service. URL: https://www.fs.usda.gov/sites/default/files/2020-08/08242020_afue_final_report.pdf.

USFS (2023). *Planes - Fire Management*. Accessed: October 2023. URL: https://www.fs.usda.gov/managing-land/fire/planes.

USFS, Forest Service (Mar. 2020a). *Aerial Firefighting Use and Effectiveness (AFUE) Report*. URL: https://www.fs.usda.gov/sites/default/files/2020-08/08242020_afue_final_report.pdf (visited on 12/08/2022).

— (2020b). *Wildland Fire Summary and Statistics Annual Report 2020*. URL: https://nifc.gov/intelligence/2020_statssumm/annual_report_2020.pdf.

— (2021). *Wildland Fire Summary and Statistics Annual Report 2021*. URL: https://nifc.gov/intelligence/2021_statssumm/annual_report_2021.pdf.

Valipour, Elmira et al. (2024). “Water Resources Allocation: Interactions Between Equity/Justice and Allocation Strategies”. en. In: *Water Resources Management* 38.2, pp. 505–535. ISSN: 0920-4741, 1573-1650. DOI: 10.1007/s11269-023-03682-y. URL: https://link.springer.com/10.1007/s11269-023-03682-y (visited on 08/17/2024).

Varela, Elsa, Jette Bredahl Jacobsen, and Mario Soliño (Oct. 2014). “Understanding the heterogeneity of social preferences for fire prevention management”. en. In: *Ecological Economics* 106, pp. 91–104. ISSN: 09218009. DOI: 10.1016/j.ecolecon.2014.07.014. URL: https://linkinghub.elsevier.com/retrieve/pii/S092180091400216X (visited on 02/08/2023).

Wakes, Sarah J. et al. (Feb. 2010). “Numerical modelling of wind flow over a complex topography”. en. In: *Environmental Modelling & Software* 25.2, pp. 237–247. ISSN: 13648152.

DOI: 10.1016/j.envsoft.2009.08.003. URL: https://linkinghub.elsevier.com/retrieve/pii/S136481520900200X (visited on 06/20/2023).

Walker, Gordon and Kate Burningham (May 2011). "Flood risk, vulnerability and environmental justice: Evidence and evaluation of inequality in a UK context". en. In: *Critical Social Policy* 31.2, pp. 216–240. ISSN: 0261-0183, 1461-703X. DOI: 10.1177/0261018310396149. URL: http://journals.sagepub.com/doi/10.1177/0261018310396149 (visited on 08/10/2022).

Walls, Margaret A. and Matthew J. Wibbenmeyer (2023). "How Local Are the Local Economic Impacts of Wildfires". In: *Resources for the Future: Washington, DC, USA*.

Wang, Daoping et al. (Dec. 2020). "Economic footprint of California wildfires in 2018". en. In: *Nature Sustainability* 4.3, pp. 252–260. ISSN: 2398-9629. DOI: 10.1038/s41893-020-00646-7. URL: https://www.nature.com/articles/s41893-020-00646-7 (visited on 03/31/2024).

Weber, Keith T. and Rituraj Yadav (Sept. 2020). "Spatiotemporal Trends in Wildfires across the Western United States (1950–2019)". en. In: *Remote Sensing* 12.18, p. 2959. ISSN: 2072-4292. DOI: 10.3390/rs12182959. URL: https://www.mdpi.com/2072-4292/12/18/2959 (visited on 03/31/2024).

Wheatley, Melanie et al. (2022). "Modelling initial attack success on forest fires suppressed by air attack in the province of Ontario, Canada". In: *International journal of wildland fire* 31.8, pp. 774–785.

White House, The (June 2022). *Justice40 Initiative Covered Programs List. Version 1.0.* URL: https://www.whitehouse.gov/wp-content/uploads/2022/06/J40-Covered-program-list_tranche1_6.24.22.pdf (visited on 07/22/2022).

White House OMB, The (Dec. 2023). *FACT SHEET: Biden-Harris Administration Announces New Initiative to Advance the Frontiers of Benefit-Cost Analysis and Strengthen Government Decision Making*. Tech. rep. URL: https://www.whitehouse.gov/omb/briefing-room/2023/12/14/fact-sheet-biden-harris-administration-announces-new-initiative-to-advance-the-frontiers-of-benefit-cost-analysis-and-strengthen-government-decision-making/ (visited on 10/24/2024).

Wibbenmeyer, Matthew J., Michael S. Hand, et al. (June 2013). "Risk Preferences in Strategic Wildfire Decision Making: A Choice Experiment with U.S. Wildfire Managers: Risk Preferences in Strategic Wildfire Decision Making". en. In: *Risk Analysis* 33.6, pp. 1021–1037. ISSN: 02724332. DOI: 10.1111/j.1539-6924.2012.01894.x. URL: https://onlinelibrary.wiley.com/doi/10.1111/j.1539-6924.2012.01894.x (visited on 12/01/2022).

Wibbenmeyer, Matthew J., Andrew J. Plantinga, and Randall Walsh (2022). *Priorities and Effectiveness in Wildfire Management: Evidence from Fire Spread in the Western US*. Type: dataset. DOI: 10.7910/DVN/HOINOA. URL: https://dataverse.harvard.edu/citation?persistentId=doi:10.7910/DVN/HOINOA (visited on 05/22/2023).

Wibbenmeyer, Matthew J. and Molly Robertson (June 2022). "The distributional incidence of wildfire hazard in the western United States". In: *Environmental Research Letters* 17.6, p. 064031. ISSN: 1748-9326. DOI: 10.1088/1748-9326/ac60d7. URL: https://iopscience.iop.org/article/10.1088/1748-9326/ac60d7 (visited on 08/09/2022).

Williams, A. Park et al. (Aug. 2019). "Observed Impacts of Anthropogenic Climate Change on Wildfire in California". en. In: *Earth's Future* 7.8, pp. 892–910. ISSN: 2328-4277, 2328-4277. DOI: 10.1029/2019EF001210. URL: https://onlinelibrary.wiley.com/doi/abs/10.1029/2019EF001210 (visited on 08/10/2022).

Wuepper, David and Robert Finger (2023). "Regression discontinuity designs in agricultural and environmental economics". In: *European Review of Agricultural Economics* 50.1, pp. 1–28.

Yen, Steven T. (Nov. 1993). "Working Wives and Food away from Home: The Box-Cox Double Hurdle Model". en. In: *American Journal of Agricultural Economics* 75.4, pp. 884–895. ISSN: 0002-9092, 1467-8276. DOI: 10.2307/1243976. URL: https://onlinelibrary.wiley.com/doi/abs/10.2307/1243976 (visited on 11/01/2022).

Yen, Steven T. and Chung L. Huang (1996). "HOUSEHOLD DEMAND FOR FINFISH: A GENERALIZED DOUBLE-HURDLE MODEL". en. In: Publisher: Unknown. DOI: 10.22004/AG.ECON.31034. URL: https://ageconsearch.umn.edu/record/31034 (visited on 11/01/2022).

Zhai, Jun et al. (2023). “Wildfire Susceptibility of Land Use and Topographic Features in the Western United States: Implications for the Landscape Management”. In: *Forests* 14.4, p. 807.

A Supplementary Materials for Chapter 2

A1 LAT drop cost calculation

In this analysis, we analyze patterns in the allocation of LAT suppression effort to communities as a function of their socioeconomic characteristics. Trends in the allocation of the effort itself are enlightening, but they won’t capture the full picture of equity if not all effort is created equal. We supplement information on the allocation of LAT drops with estimates on how LAT expenses are distributed amongst different communities. This part of our analysis will capture if LATs with larger tanks are used to suppress fire in more wealthy and white communities or if more “expensive” planes are used in those neighborhoods.

We are able to calculate the cost of each drop using restricted data from the Forest Service on payments to aviation contractors for the use of their LATs. This data is structured at plane-day-expense[83] level, containing information on the amount of retardant released by the aircraft, their time spent flying that day, and any “availability” charges for keeping the resource on standby. These data also reveal the model of aircraft that is allocating retardant drops. We collapse this information down to the plane-day level.

Unfortunately, this data is not available across our entire sample period (only 2020), so we must develop a method to calculate the cost of LAT drops for the other years in our sample (2017 to 2019). We collapse the data on LAT drops down to the plane-day level to remain consistent between the two data sources. This collapsed data now shows how many drops were released by each plane on a given day, how many gallons of retardant it released, and the model of aircraft.

We subset our collapsed data on LAT drops to 2020, as that is the only year we have data on aviation expenses. Then we use a random forest learning algorithm to fit the LAT costs onto

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[83] For example, Plane X will have a row for the fuel costs of its time spent flying. It will have a separate row for charges from the retardant used.

Table A1: Means table for census tracts in our sample

	All Tracts[1]	WHP > 3 Tracts[2]	Aviation Tracts[3]	No Aviation Tracts[4]
Tract Identified as 'Disadvantaged'	0.254	0.288	0.342	0.213
Share of tracts which received aviation effort	0.321	0.475	1.000	0.000
Count of Aviation Drops Received (2017 - 2020)	23.584	38.720	51.317	10.447
Minority %	0.267	0.258	0.245	0.277
Low-Income %	0.299	0.300	0.324	0.288
Median Income (percentile rank of sample)	0.500	0.492	0.452	0.523
Pop. % Over 64 y.o	0.207	0.228	0.229	0.197
White %	0.833	0.831	0.829	0.834
Black %	0.015	0.014	0.011	0.017
Native %	0.042	0.049	0.057	0.035
Asian Pop. %	0.034	0.029	0.028	0.036
Hispanic Pop. %	0.176	0.165	0.154	0.186
Population Density (percentile rank of sample)	0.500	0.501	0.410	0.542
Wildfire Hazard Potential (percentile rank of sample)	0.499	0.833	0.612	0.445
Burn Probability (percentile rank of sample)	0.500	0.743	0.604	0.451
Elevation (percentile rank of sample)	0.500	0.546	0.563	0.470
Terrain Ruggedness Index (percentile rank of sample)	0.500	0.676	0.602	0.452
USFS Land Share	0.177	0.306	0.260	0.138
BLM Land Share	0.094	0.099	0.130	0.077
NPS Land Share	0.015	0.005	0.015	0.016
FWS Land Share	0.003	0.000	0.003	0.002
BIA Land Share	0.000	0.000	0.000	0.000
Water Threshold Exceeded	0.013	0.019	0.011	0.014
Workforce Threshold Exceeded	0.103	0.131	0.142	0.084
Climate Threshold Exceeded	0.163	0.227	0.233	0.129
Energy Threshold Exceeded	0.094	0.088	0.122	0.080
Traffic Threshold Exceeded	0.004	0.000	0.000	0.005
Housing Threshold Exceeded	0.009	0.003	0.000	0.013
Pollution Threshold Exceeded	0.007	0.008	0.008	0.007
Health Threshold Exceeded	0.118	0.147	0.175	0.091
Observations	1120	375	713	407

[1] Contains the means for the variables in our analysis for the entire sample of our analysis, all fire-affected census tracts from 2017 to 2020. All percentages are reported as decimals.

[2] Contains means for all census tracts in our sample with a wildfire hazard potential greater than 3.

[3] Contains means for all census tracts in our sample that receive suppression effort from aviation.

[4] Contains means for all census tracts in our sample that don't receive suppression effort from aviation.

the data on LAT drops using information on aircraft type, number of drops[84], and total retardant used. We can then take those predictions and use them with the other years of LAT drops we have, calculating the daily expenses incurred by each LAT in our sample from 2017 to 2019.

The plane-level costs will give us a sense of how the cost of LAT suppression is distributed among different wildfires, but it won't reveal anything about patterns of allocation across communities. We need the costs of individual retardant drops for that analysis. Equation 10 below shows how we calculate the cost of individual drops -

$$\text{Costs}_i = (\frac{\text{Gal}_i}{\text{TotalGal}_{pd}})\hat{\text{PC}}_{pd} \tag{5}$$

The drop-level cost (Costs_i) is calculated by dividing the daily expenses for each plane (PC_{pd}) by the total amount of retardant it released that day (TotalGal_{pd}). This gives us a daily "cost per gallon of retardant" for each LAT in our sample[85]. Then we calculate the cost for each drop by multiplying the number of gallons of retardant (Gal_i) in it by the daily per-unit retardant cost that is plane-specific.

The amount of LAT suppression investment allocated to each community is calculated once we estimate a cost for each drop in our sample. We determine this level of investment similar to how we calculate the level of suppression effort allocated to a community; we overlay our drops with a map of our fire-affected census tracts, then total the cost of all of the drops released in that community.

Modeling the relationship with LAT expenses will capture any spatial trends in the allocation of LAT dollars on a community-by-community basis. If two identical communities were threatened by a wildfire, and they differed only in that one had a higher share of minority residents, then we might conclude that suppression effort allocations were equitable if they both received twelve retardant drops. However, if the community with a lower share of minority residents received all

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[84] Unfortunately, we do not have information on flight time in the drops data from ATUs. We choose to use the number of drops released as a proxy for flight time, as it will represent how many "trips" the aircraft took that day.

[85] The way this random forest model is set up allows for the type of plane and flight time to be backed into the per-unit retardant cost, given our assumptions.

Table A2: Dependent Variable: Hurdle model **marginal effects** (census tract-level analysis)

	(1) LAT Drops	(2) LAT Drops	(3) LAT drops	(4) LAT costs	(5) LAT costs	(6) LAT costs
Minority %	-22.324** (9.333)	3.981 (8.329)	3.433 (8.077)	-125281.097* (65713.925)	65548.669 (54928.321)	62454.293 (54087.616)
Low-Income %	23.625* (12.128)	-2.464 (11.265)	-3.780 (11.111)	123131.737 (83856.961)	-48865.525 (70812.531)	-59377.271 (68987.321)
Over 64 y.o. %	31.631 (20.275)	1.292 (11.085)	5.346 (12.012)	308236.391* (163032.113)	45281.439 (89308.190)	73895.125 (100698.302)
Unemployment Rate	46.358** (22.303)	-11.586 (16.059)	-15.394 (16.972)	357633.800** (157807.033)	-34835.036 (105589.020)	-60264.526 (110345.666)
Median Income ($1000s)	-135.329* (75.225)	51.076 (70.547)	9.872 (68.333)	-994351.275* (531968.055)	355824.653 (474418.354)	83121.462 (453448.779)
'Disadvantaged' Community	5.066 (4.271)	5.456* (3.159)	5.378* (2.987)	31694.836 (29806.962)	34155.750 (22467.574)	33400.719 (21009.204)
Land management controls (binned)	No	Yes	Yes	No	Yes	Yes
Biophysical controls (binned)	No	Yes	Yes	No	Yes	Yes
Population density controls (binned)	No	Yes	Yes	No	Yes	Yes
GACC fixed effects	No	No	Yes	No	No	Yes
Observations	1,102	1,102	1,102	1,102	1,102	1,102

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of their retardant drops from a plane with an 8000-gallon tank while the other community received them from a tanker with a 3000-gallon tank, that would suggest inequity. This additional dependent variable in our models will aid in determining if that is systematically occurring.

A2 Fire-level sample

Conducting our analysis using a data set of over 1100 census tracts allows us to evaluate if there are significant inequities in our system of wildfire resource allocation, but may leave us

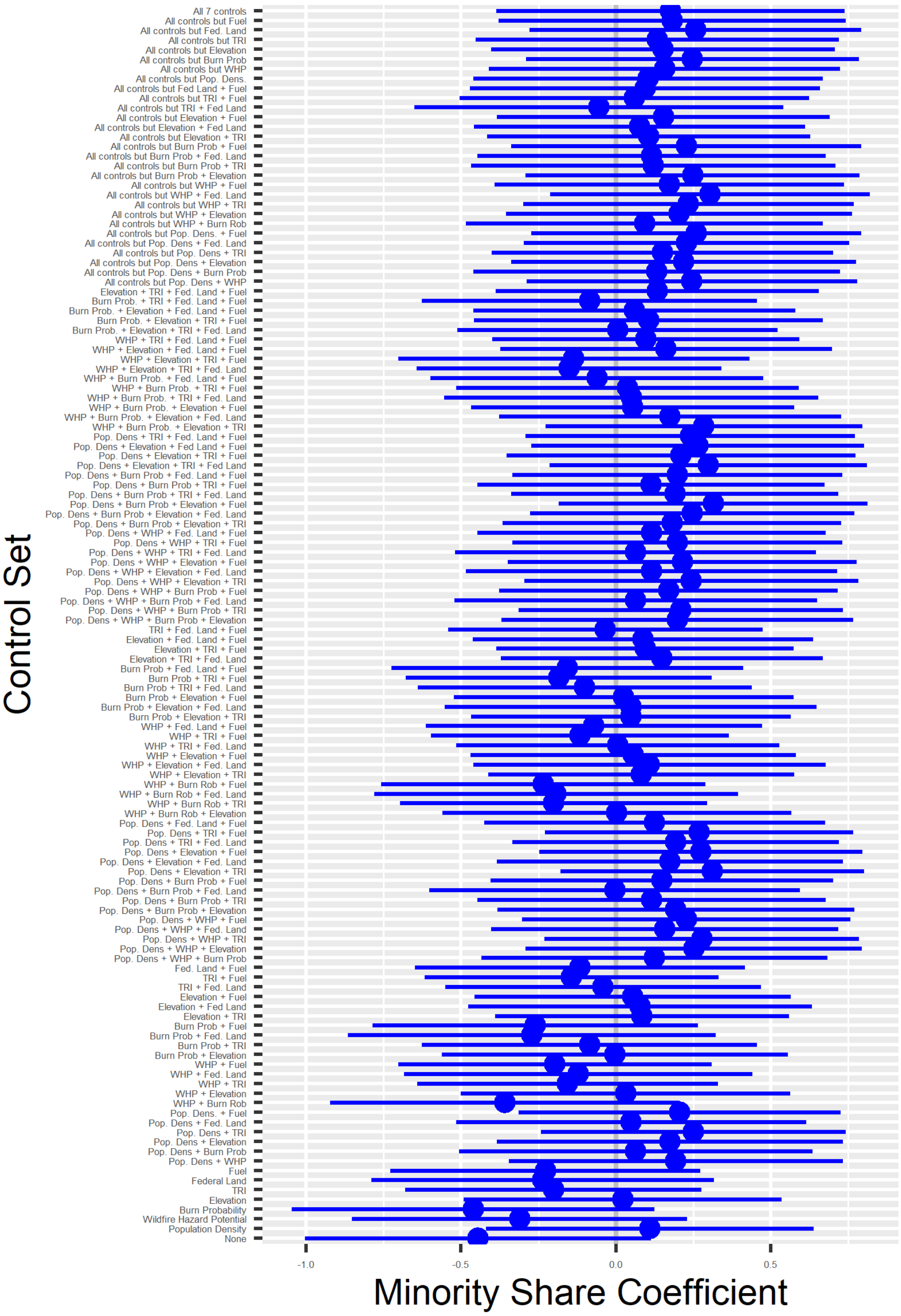

Figure A1: Dot-Whisker plot of the coefficient estimate on the minority population share variable in Table 2 (intensive margin impact), based on factors conditioned on.

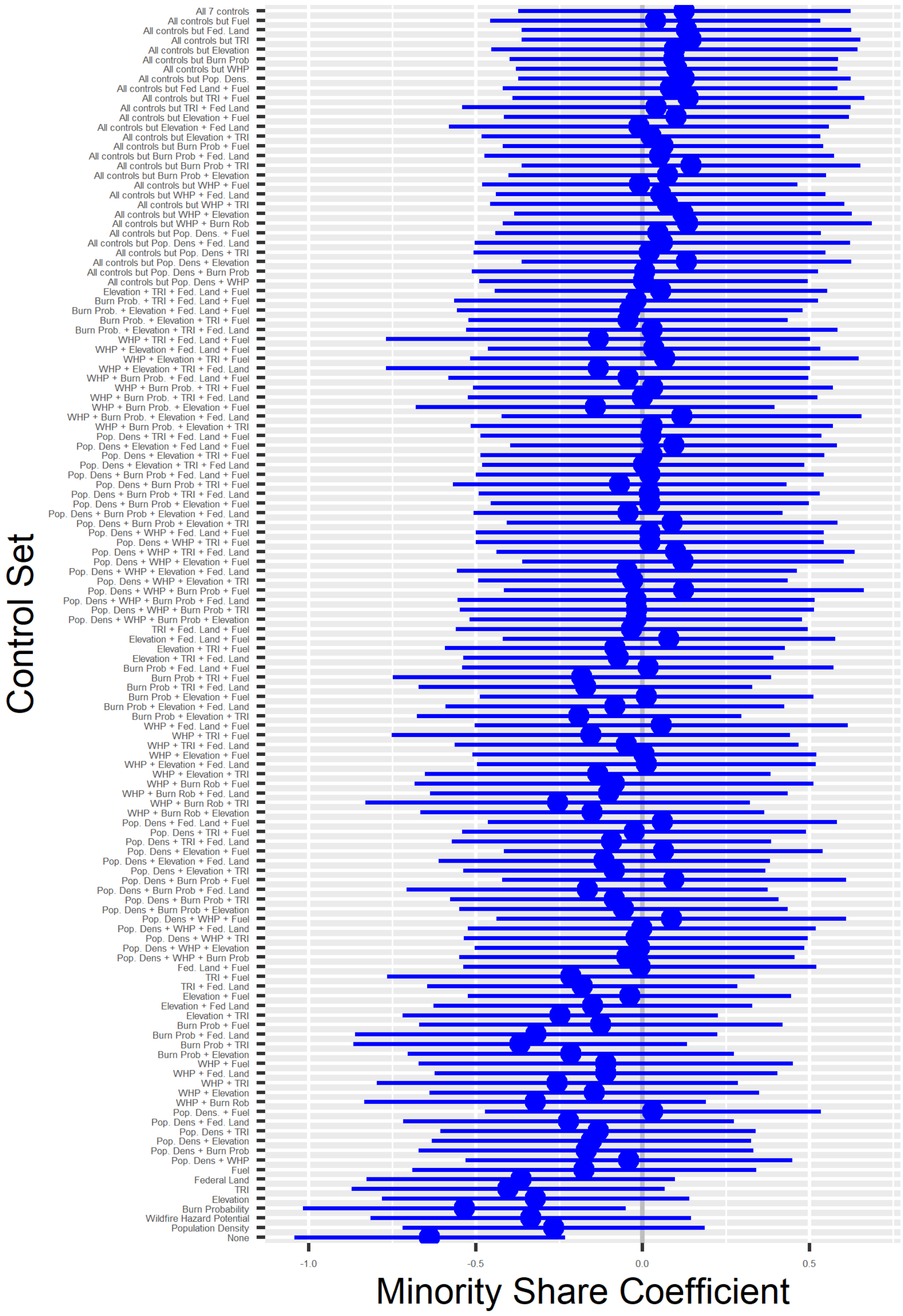

Figure A2: Dot-Whisker plot of the coefficient estimate on the minority population share variable in Table 2 (extensive margin impact), based on factors conditioned on.

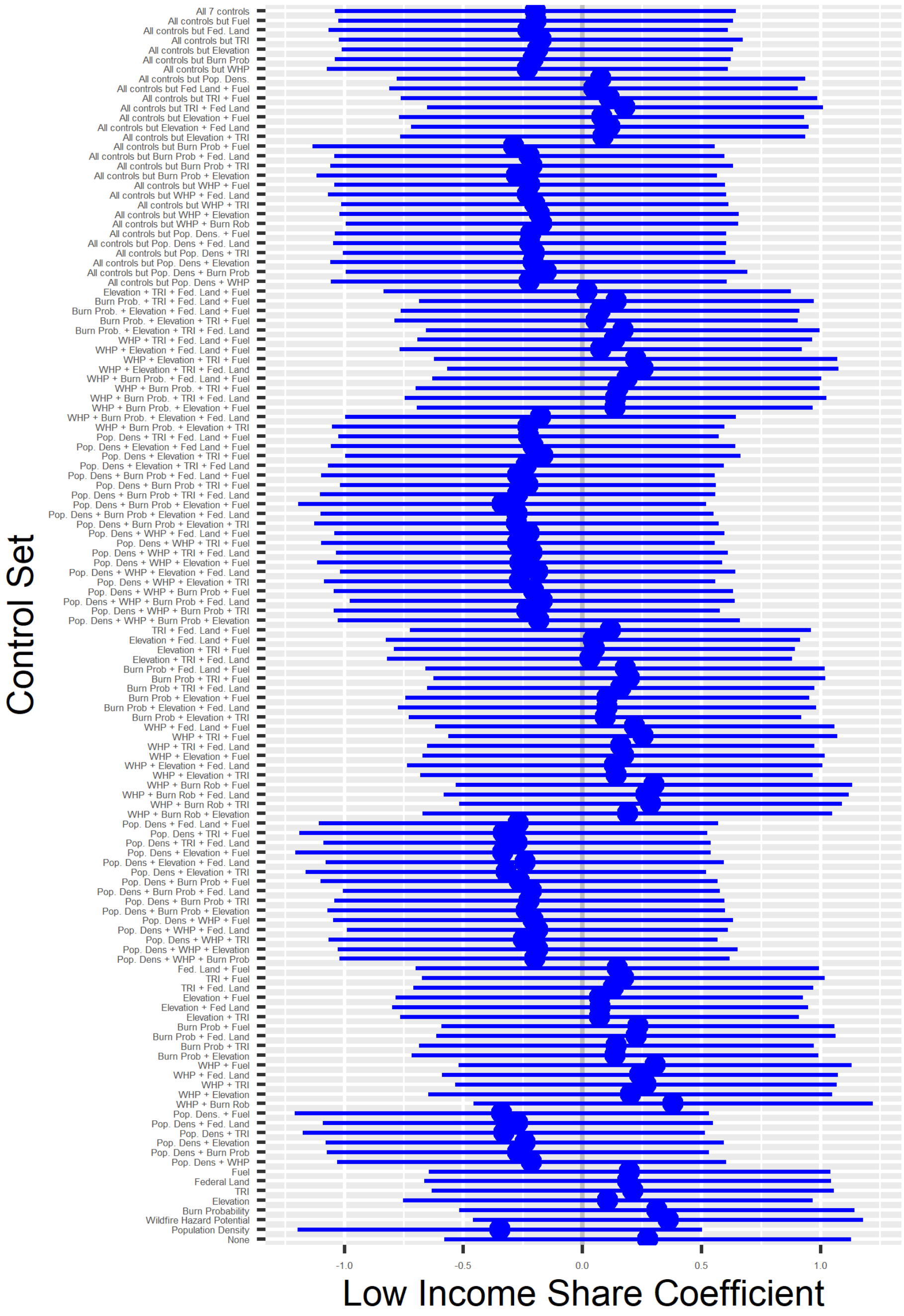

Figure A3: Dot-Whisker plot of the coefficient estimate on the low-income population share variable in Table 2 (extensive margin impact), based on factors conditioned on.

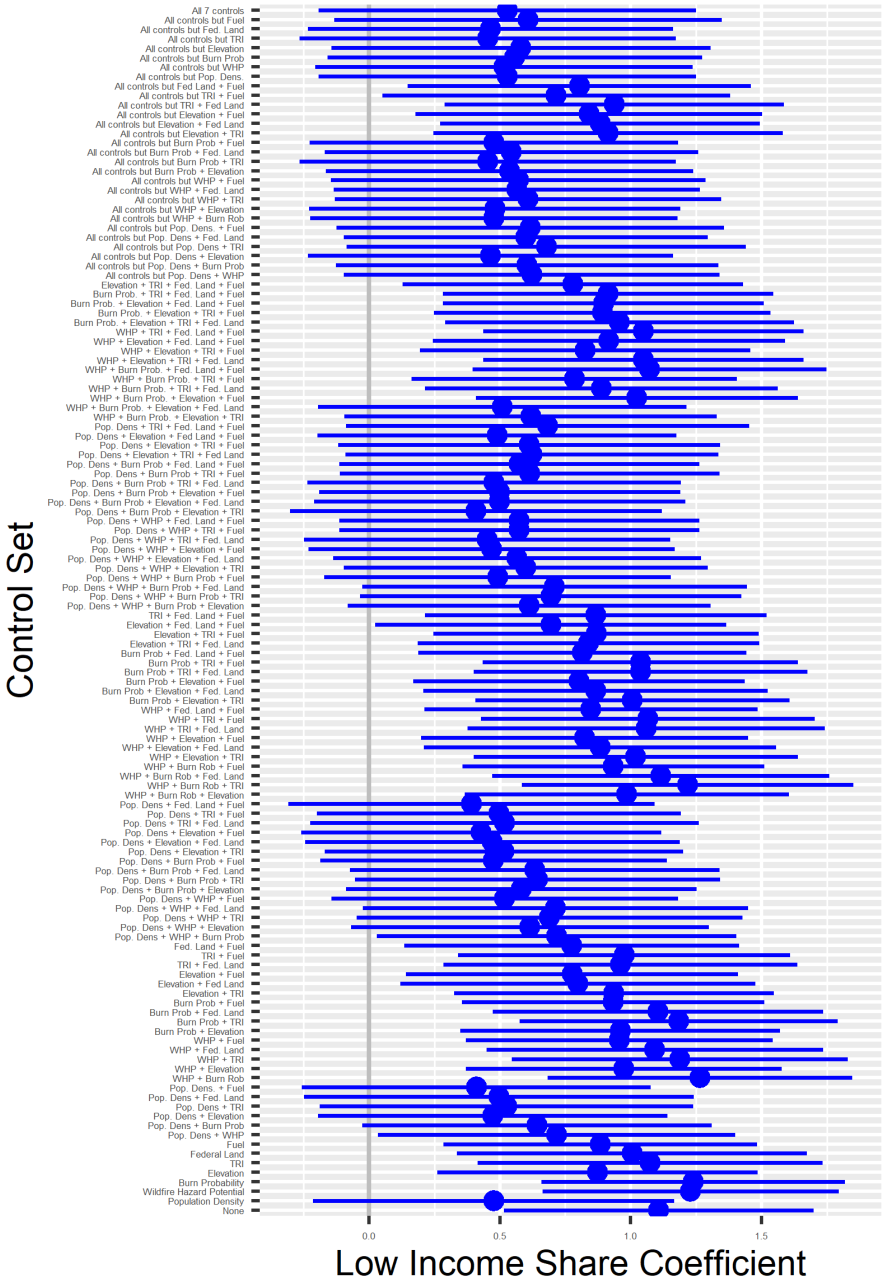

Figure A4: Dot-Whisker plot of the coefficient estimate on the low-income population share variable in Table 2 (intensive margin impact) based on factors conditioned on.

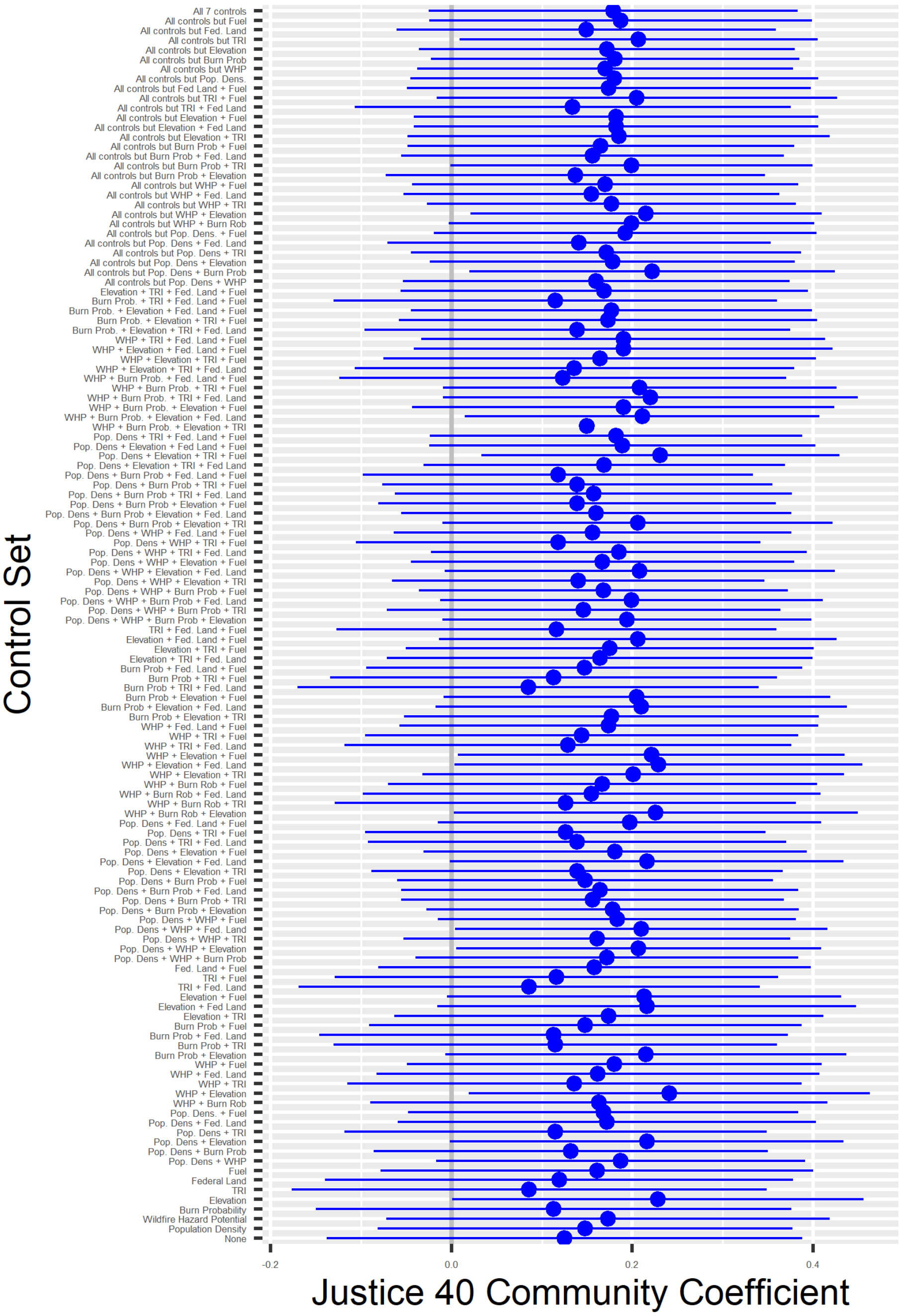

Figure A5: Dot-Whisker plot of the coefficient estimate on the Justice 40 community variable in Table 2 (extensive margin impact), based on factors conditioned on.

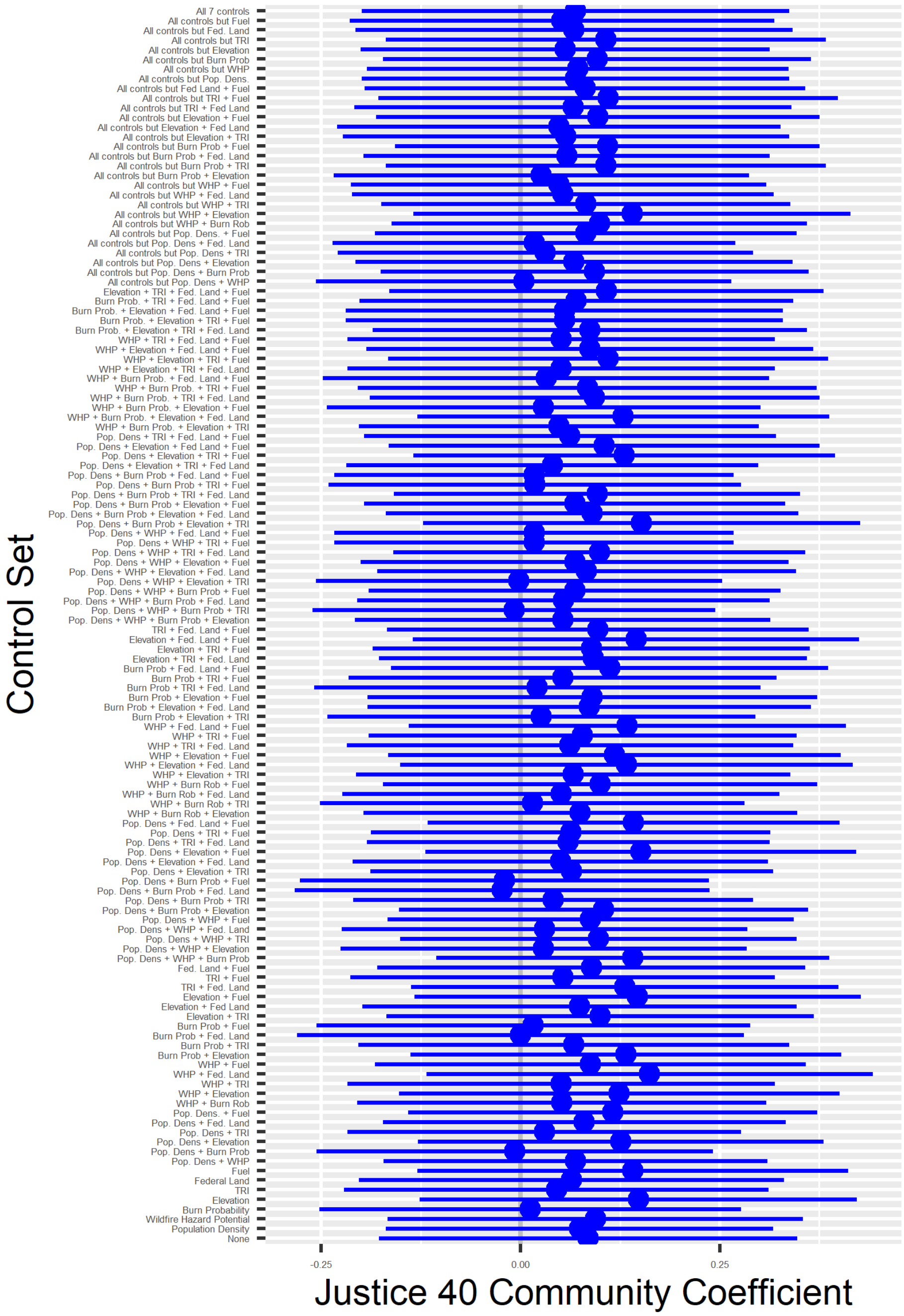

Figure A6: Dot-Whisker plot of the coefficient estimate on the Justice 40 community variable in Table 2 (intensive margin impact), based on factors conditioned on.

with more questions regarding the mechanism(s) driving that inequity. It's possible that we will find evidence that minority residents are negatively correlated with the likelihood of receiving suppression effort. If that's the case, that inequity could be created from within-fire decisions about the spatial allocation of suppression effort. It could also be a function of across-fire dispatching decisions by the regional office. We create a dataset at the fire level to address the equity of resource decisions made by the regional office (GACC).

The misallocation of resources along socioeconomic lines is much more intuitive to consider at the community scale than at the fire. Communities are frequently defined by their social, ethnic, and/or economic characteristics. A census tract's (or block group's) relatively small spatial extent makes its unique characteristics more recognizable and aids in their measurement. The fires in our sample, however, can cover significant spatial ranges[86]. Defining the socioeconomic characteristics of an entire population of people threatened by a wildfire is not as straightforward. To do so, we collapse all of our socioeconomic variables to the fire based on the census tracts that it spread into, weighted by the tract's population.

We continue to use our data on LAT retardant drops as a measure of suppression effort. For each fire in our sample, we total the number of drops released while a plane was assigned to that incident. We also measure the number of unique airplanes dispatched to an individual fire. We obtained data from the Forest Service on denied requests (also called "unable to fulfill request" or UTFs) of large airtankers by incident management teams. We use the fire's final perimeter to extract data for the same biophysical covariates as we do with the census tract sample.

Table A3 below shows summary statistics for key variables in the fire-level analysis. Tables 2.2 and 2.3 in the main text show the results of this analysis.

A3 Heterogeneity Analysis

We expanded our analysis to consider that the influence of socioeconomic factors on wildfire suppression efforts might vary across different racial/ethnic groups or different types of environ-

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[86] The 2020 Cameron Peak fire in Colorado (see the right panel of Figure 2.2) burned an area larger than the size of all five boroughs of New York City.

Table A3: Summary statistics for Census tracts with drops

	All Fires Mean	Fires w/ drops Mean	Fires w/o drops Mean
Total LAT Costs ($)	153125.760	169276.541	0.000
Total LAT Drops	23.022	25.450	0.000
Total LATs	3.350	3.704	0.000
Total Requests	1.269	1.389	0.139
Weighted Total Requests	0.711	0.772	0.139
Minority %	0.204	0.222	0.033
Low-Income %	0.291	0.314	0.074
Unemployment Rate	0.288	0.288	0.313
Median Income	57345.867	57576.294	48085.560
Black %	0.011	0.011	0.009
Native %	0.067	0.067	0.069
Asian %	0.014	0.014	0.016
Hispanic %	0.153	0.155	0.089
Observations	828	749	79

mental disadvantage. It's possible there could be a correlation with a specific ethnic minority group(s), even though our baseline Hurdle model specification suggests that race is not correlated with decisions to use aviation in wildfire suppression. We repeated an estimation of our entire model in Table 2.1 (Column 4), replacing our original measure of a census tract's minority population share with information specific for the population Black, Native American, Asian, and Hispanic residents. This allows us to determine whether there is heterogeneity in LAT allocations by minority group. Figure A7 provides a visual depiction of the coefficients on the different minority group variables for the extensive and intensive margin measures of suppression effort. Table A6 in the Appendix provides the coefficient estimates for both binary and continuous portions of our Hurdle model. Our results suggest that there isn't any correlation between any particular racial group and either the intensive or extensive margin measures of aerial suppression effort.

We estimate another model where we test for heterogeneity in the "environmentally disadvantaged" designation by the federal government. The binary indicator for that designation is replaced with a series of eight binary indicators, one for each threshold by which a community could qualify for explicit federal funding. Figure A8 shows the coefficient estimates of the correlation between

Table A4: Hurdle model estimation of the correlation of LAT wildfire suppression with socioeconomic characteristics of a community (Census Block Group level)

	(1) LAT Drops	(2) LAT Drops	(3) LAT drops	(4) LAT costs	(5) LAT costs	(6) LAT costs
Intensive						
Minority %	-0.157	0.472***	0.542***	-0.162	0.466***	0.564***
	(0.170)	(0.163)	(0.165)	(0.177)	(0.168)	(0.167)
Low-Income %	-1.266**	-1.282***	-1.302***	-1.011*	-0.967**	-0.982**
	(0.519)	(0.450)	(0.443)	(0.566)	(0.455)	(0.443)
Over 64 y.o. %	0.104	-0.027	0.033	0.185	0.001	0.080
	(0.469)	(0.479)	(0.509)	(0.496)	(0.467)	(0.498)
Unemployment Rate	1.129	0.494	0.686	-0.106	-0.612	-0.481
	(1.194)	(1.176)	(1.197)	(1.276)	(1.241)	(1.256)
Median Income	-8.538***	-1.948	-2.083	-8.113***	-1.171	-1.221
	(1.748)	(1.747)	(1.692)	(1.990)	(1.937)	(1.858)
'Disadvantaged' Community	0.272**	0.118	0.129	0.201	0.078	0.082
	(0.120)	(0.109)	(0.108)	(0.123)	(0.104)	(0.102)
Extensive						
Minority %	-0.248	0.219	0.338*	-0.311	0.164	0.274
	(0.195)	(0.191)	(0.193)	(0.196)	(0.181)	(0.174)
Low-Income %	1.119**	1.007*	1.056**	1.033**	0.737	0.761
	(0.460)	(0.559)	(0.537)	(0.476)	(0.573)	(0.559)
Over 64 y.o. %	0.460	0.020	0.328	0.447	-0.020	0.303
	(0.478)	(0.399)	(0.356)	(0.480)	(0.399)	(0.358)
Unemployment Rate	-0.058	0.438	0.591	0.127	0.938	1.090
	(0.903)	(1.029)	(1.065)	(0.903)	(1.044)	(1.057)
Median Income	-0.527	2.723**	2.877***	-1.023	2.580**	2.530**
	(1.509)	(1.201)	(1.099)	(1.471)	(1.140)	(1.108)
'Disadvantaged' Community	0.243**	-0.132	-0.143	0.296**	-0.032	-0.038
	(0.118)	(0.120)	(0.126)	(0.120)	(0.122)	(0.127)
Land management controls (binned)	No	Yes	Yes	No	Yes	Yes
Biophysical controls (binned)	No	Yes	Yes	No	Yes	Yes
Population density controls (binned)	No	Yes	Yes	No	Yes	Yes
GACC fixed effects	No	No	Yes	No	No	Yes
Observations	1,647	1,647	1,647	1,647	1,647	1,647

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Dependent Variable: Hurdle model **marginal effects** (census block group-level analysis)

	(1) LAT Drops	(2) LAT Drops	(3) LAT drops	(4) LAT costs	(5) LAT costs	(6) LAT costs
Minority %	-5.770	8.809***	10.488***	-44210.976	55016.278***	68795.027***
	(3.990)	(2.717)	(2.605)	(27797.990)	(18912.112)	(18537.625)
Low-Income %	-7.851	-15.783**	-15.909**	-28057.741	-79008.905	-79955.977
	(10.051)	(7.727)	(7.586)	(71573.226)	(50323.562)	(48828.974)
Over 64 y.o. %	7.496	-0.341	2.171	58115.236	-552.240	18241.162
	(10.518)	(8.229)	(8.633)	(72257.862)	(51559.210)	(54839.081)
Unemployment Rate	18.651	10.289	14.093	-1422.713	-34599.171	-16184.928
	(24.849)	(19.751)	(19.784)	(170441.334)	(136461.762)	(135803.588)
Median Income	-152.998***	-17.921	-19.548	-999964.477***	-40446.709	-48612.989
	(42.501)	(27.067)	(25.611)	(301749.723)	(200273.379)	(187613.642)
SM$_C$	7.682***	1.253	1.384	47323.578**	7243.327	7540.903
	(2.802)	(1.793)	(1.814)	(18889.284)	(11145.083)	(11065.156)
Land management controls (binned)	No	Yes	Yes	No	Yes	Yes
Biophysical controls (binned)	No	Yes	Yes	No	Yes	Yes
Population density controls (binned)	No	Yes	Yes	No	Yes	Yes
GACC fixed effects	No	No	Yes	No	No	Yes
Observations	1,647	1,647	1,647	1,647	1,647	1,647

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

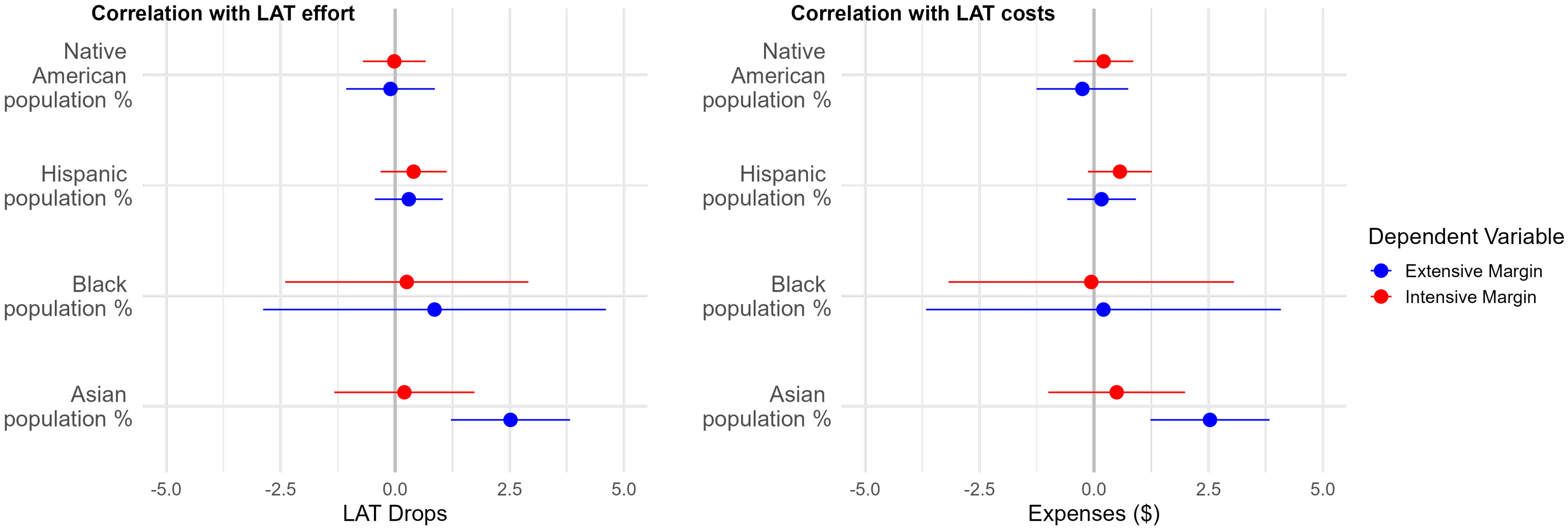

Figure A7: Heterogeneity in the correlation between minority % and LAT allocations based on racial group our eight different community indicators on the likelihood of aerial suppression effort received (corresponds to Table A7 in the appendix); Figure A8 also displays the comparable coefficients for the amount of aerial suppression. Our results indicate that a few of the categories that can designate a community as “environmentally disadvantaged" are significantly correlated with the likelihood of receiving aviation: the “traffic” and “health burdens” categories. None of the Justice 40 categories appear to be correlated with the amount of aviation received by a fire-affected community.

If a tract qualifies based on exceeding the traffic proximity threshold, it will be above the 90th percentile of communities in diesel particulate matter, traffic volume, or transportation barriers. We estimate a coefficient of less than 3 on the extensive margin impact of exceeding the traffic threshold (See Figure A8). This means that conditional on receiving suppression effort from a LAT in the first place, tracts qualifying on the basis of the traffic criteria will be 2.7 times more likely (see Table A7) to receive aerial suppression effort. This increased likelihood does not correspond to an increased magnitude.

If a census tract qualifies for additional federal investment because it surpasses the “health burdens” threshold, that would mean that the tract was above the 90th percentile in either asthma, diabetes, or heart disease rates or from being above the 90th percentile in low life expectancy. Figure A8 also shows intensive margin estimates indicating that a community surpassing the “health burdens” threshold would be 35% less likely to receive a retardant drop.

Table A6: Dependent Variable: Hurdle model estimation with demographic heterogeneity

	(1) LAT drops	(2) LAT drops	(3) LAT costs	(4) LAT costs
Intensive				
Minority %	0.086		0.340	
	(0.292)		(0.280)	
Low-Income %	-0.259	-0.163	-0.484	-0.361
	(0.416)	(0.402)	(0.369)	(0.372)
Over 64 y.o. %	0.217	0.409	0.547	0.621
	(0.411)	(0.373)	(0.522)	(0.473)
Unemployment Rate	-0.773	-0.611	-0.460	-0.271
	(0.616)	(0.576)	(0.578)	(0.533)
Median Income ($1000s)	-0.562	0.481	-0.557	0.504
	(2.714)	(2.953)	(2.591)	(2.830)
'Disadvantaged' Community	0.202^{*}	0.141	0.164	0.106
	(0.115)	(0.115)	(0.117)	(0.119)
Black %		0.255		-0.059
		(1.355)		(1.590)
Native %		-0.018		0.211
		(0.350)		(0.332)
Asian %		0.202		0.496
		(0.781)		(0.762)
Hispanic %		0.404		0.567
		(0.368)		(0.357)
Extensive				
Minority %	0.209		0.042	
	(0.233)		(0.276)	
Low-Income %	0.520	0.696^{*}	0.676^{*}	0.858^{**}
	(0.367)	(0.382)	(0.397)	(0.393)
Over 64 y.o. %	-0.056	0.007	-0.592	-0.443
	(0.588)	(0.608)	(0.439)	(0.445)
Unemployment Rate	0.834	0.825	0.544	0.511
	(0.600)	(0.669)	(0.581)	(0.651)
Median Income ($1000s)	4.290^{**}	2.741	4.534^{**}	2.912
	(2.104)	(2.536)	(1.940)	(2.363)
'Disadvantaged' Community	0.021	-0.006	0.104	0.081
	(0.136)	(0.142)	(0.140)	(0.146)
Black %		0.861		0.207
		(1.910)		(1.977)
Native %		-0.100		-0.253
		(0.494)		(0.511)
Asian %		2.521^{***}		2.534^{***}
		(0.850)		(0.766)
Hispanic %		0.300		0.165
		(0.379)		(0.383)
Observations	1,102	1,102	1,102	1,102

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Dependent Variable: Hurdle model estimation with disadvantaged designation heterogeneity

	(1) LAT drops	(2) LAT drops	(3) LAT costs	(4) LAT costs
Intensive				
Minority %	0.086	0.237	0.340	0.465
	(0.292)	(0.324)	(0.280)	(0.312)
Low-Income %	-0.259	-0.173	-0.484	-0.394
	(0.416)	(0.412)	(0.369)	(0.372)
Over 64 y.o. %	0.217	0.273	0.547	0.598
	(0.411)	(0.446)	(0.522)	(0.592)
Unemployment Rate	-0.773	-0.279	-0.460	-0.153
	(0.616)	(0.589)	(0.578)	(0.566)
Median Income	-0.562	0.164	-0.557	-0.344
	(2.714)	(2.624)	(2.591)	(2.569)
’Disadvantaged’ Community	0.202*	0.272	0.164	0.166
	(0.115)	(0.196)	(0.117)	(0.186)
Water Threshold Exceeded		0.035		-0.004
		(0.368)		(0.381)
Workforce Threshold Exceeded		-0.243		-0.248
		(0.196)		(0.200)
Climate Threshold Exceeded		0.304		0.341*
		(0.189)		(0.199)
Energy Threshold Exceeded		-0.024		0.014
		(0.194)		(0.198)
Traffic Threshold Exceeded		2.771***		2.891***
		(0.667)		(0.532)
Housing Threshold Exceeded		-0.788		-0.970**
		(0.549)		(0.416)
Pollution Threshold Exceeded		-0.161		-0.152
		(0.321)		(0.339)
Health Threshold Exceeded		-0.464***		-0.368**
		(0.160)		(0.162)
Extensive				
Minority %	0.209	0.109	0.042	-0.127
	(0.233)	(0.278)	(0.276)	(0.345)
Low-Income %	0.520	0.391	0.676*	0.547
	(0.367)	(0.370)	(0.397)	(0.405)
Over 64 y.o. %	-0.056	-0.043	-0.592	-0.617
	(0.588)	(0.587)	(0.439)	(0.444)
Unemployment Rate	0.834	0.684	0.544	0.251
	(0.600)	(0.728)	(0.581)	(0.690)
Median Income	4.290**	4.312**	4.534**	4.449**
	(2.104)	(2.177)	(1.940)	(2.004)
’Disadvantaged’ Community	0.021	-0.254	0.104	-0.200
	(0.136)	(0.211)	(0.140)	(0.227)
Water Threshold Exceeded		0.389		0.470
		(0.497)		(0.467)
Workforce Threshold Exceeded		0.265		0.381
		(0.249)		(0.281)
Climate Threshold Exceeded		0.175		0.080
		(0.243)		(0.247)
Energy Threshold Exceeded		0.288		0.293*
		(0.184)		(0.175)
Traffic Threshold Exceeded		0.425		0.569
		(0.411)		(0.388)
Housing Threshold Exceeded		0.472		0.328
		(0.415)		(0.397)
Pollution Threshold Exceeded		-0.718*		-0.686*
		(0.435)		(0.412)
Health Threshold Exceeded		-0.042		0.087
		(0.187)		(0.203)
Observations	1,102	1,102	1,102	1,102

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Hurdle model estimation of the correlation of LAT wildfire suppression with socioeconomic characteristics of a community using subset of drops with retardant volume information (Census Tract level)

	(1) LAT Drops	(2) LAT Drops	(3) LAT drops	(4) LAT costs	(5) LAT costs	(6) LAT costs
Intensive						
Minority %	-0.373	0.256	0.267	-0.296	0.378	0.385
	(0.287)	(0.270)	(0.279)	(0.278)	(0.264)	(0.278)
Low-Income %	0.164	-0.199	-0.225	0.004	-0.355	-0.387
	(0.446)	(0.383)	(0.387)	(0.438)	(0.363)	(0.363)
Over 64 y.o. %	1.261**	0.438	0.561	1.365**	0.478	0.604
	(0.618)	(0.447)	(0.510)	(0.658)	(0.474)	(0.533)
Unemployment Rate	0.854	-0.180	-0.233	0.820	-0.182	-0.253
	(0.618)	(0.526)	(0.546)	(0.608)	(0.519)	(0.534)
Median Income ($1000s)	-0.006***	0.001	-0.001	-0.006***	0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
'Disadvantaged' Community	0.068	0.146	0.133	0.089	0.166	0.151
	(0.135)	(0.106)	(0.103)	(0.136)	(0.110)	(0.107)
Extensive						
Minority %	-0.687**	0.078	0.004	-0.687**	0.078	0.004
	(0.300)	(0.306)	(0.272)	(0.300)	(0.306)	(0.272)
Low-Income %	1.209***	0.782**	0.754*	1.209***	0.782**	0.754*
	(0.327)	(0.398)	(0.387)	(0.327)	(0.398)	(0.387)
Over 64 y.o. %	0.501	-0.727*	-0.609	0.501	-0.727*	-0.609
	(0.572)	(0.422)	(0.419)	(0.572)	(0.422)	(0.419)
Unemployment Rate	2.011***	0.681	0.693	2.011***	0.681	0.693
	(0.738)	(0.623)	(0.615)	(0.738)	(0.623)	(0.615)
Median Income ($1000s)	0.002	0.005**	0.004*	0.002	0.005**	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
'Disadvantaged' Community	0.146	0.079	0.111	0.146	0.079	0.111
	(0.136)	(0.130)	(0.138)	(0.136)	(0.130)	(0.138)
Land management controls (binned)	No	Yes	Yes	No	Yes	Yes
Biophysical controls (binned)	No	Yes	Yes	No	Yes	Yes
Population density controls (binned)	No	Yes	Yes	No	Yes	Yes
GACC fixed effects	No	No	Yes	No	No	Yes
Observations	1,102	1,102	1,102	1,102	1,102	1,102

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Dependent Variable: Hurdle model **marginal effects** using subset of drops with retardant volume information (census tract-level analysis)

	(1) LAT Drops	(2) LAT Drops	(3) LAT drops	(4) LAT costs	(5) LAT costs	(6) LAT costs
Minority %	-19.962**	7.030	6.861	-125385.787*	70594.487	68553.548
	(9.456)	(7.682)	(7.659)	(65793.478)	(52661.876)	(53378.823)
Low-Income %	21.892*	-0.482	-1.549	123425.301	-31266.573	-39875.983
	(11.853)	(10.005)	(10.019)	(83655.485)	(67456.055)	(66496.440)
Over 64 y.o. %	41.136*	6.950	10.974	307280.312*	55446.173	84075.089
	(22.228)	(12.392)	(14.026)	(162782.625)	(90763.977)	(101424.737)
Unemployment Rate	52.030**	-0.587	-2.113	358076.038**	-4621.023	-18416.046
	(22.595)	(14.755)	(14.926)	(157753.820)	(100932.876)	(101725.491)
Median Income ($1000s)	-0.138*	0.044	0.007	-992.672*	280.085	31.815
	(0.074)	(0.060)	(0.060)	(528.803)	(439.002)	(424.272)
'Disadvantaged' Community	3.929	4.208	4.014	31463.804	32773.949	31041.634
	(4.177)	(2.728)	(2.638)	(29766.722)	(19943.673)	(18994.678)
Land management controls (binned)	No	Yes	Yes	No	Yes	Yes
Biophysical controls (binned)	No	Yes	Yes	No	Yes	Yes
Population density controls (binned)	No	Yes	Yes	No	Yes	Yes
GACC fixed effects	No	No	Yes	No	No	Yes
Observations	1,102	1,102	1,102	1,102	1,102	1,102

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

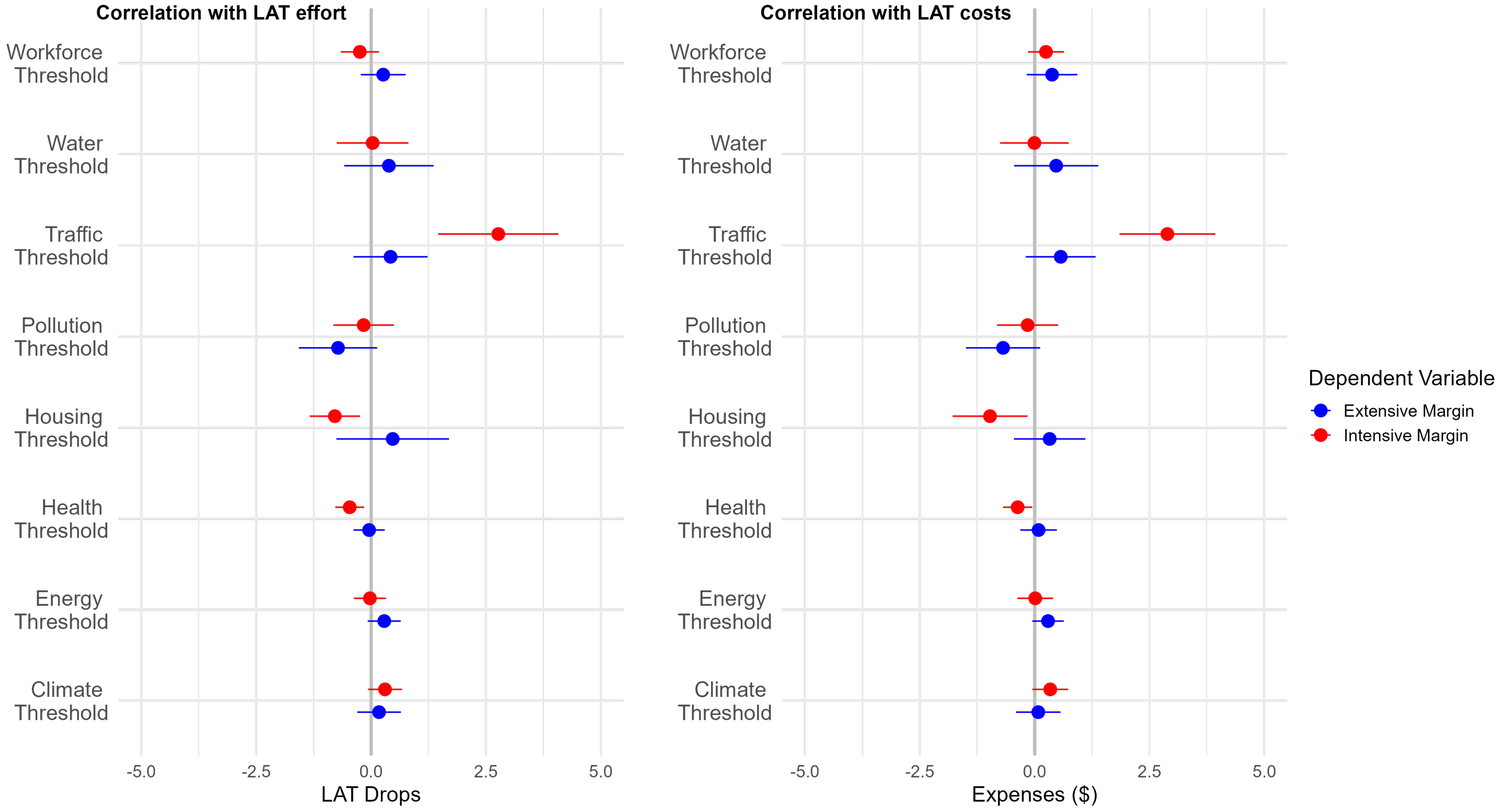

Figure A8: Heterogeneity in the correlation between Justice 40 designation and LAT allocations based on threshold qualified on

B Supplementary Materials for Chapter 3

Table B1: List of media-distracting events in this analysis

Date of Event	Location	Description
Aug 11, 2017	Charlottesville, VA	White supremacist rally that resulted in the death of one protestor.
October 1, 2017	Las Vegas, NV	Mass shooting at a music festival resulting in 58 deaths.
October 15, 2017	N/A	Date of first #MeToo tweet raising awareness of sexual misconduct.
November 5, 2017	Sutherland Springs, TX	Mass shooting at a church resulting in 25 deaths.
February 14, 2018	Parkland, FL	Mass shooting at Parkland High School resulting in 17 deaths.
May 18, 2018	Santa Fe, TX	Mass shooting at Santa Fe High School resulting in 10 deaths.
October 27, 2018	Pittsburgh, PA	Mass shooting at a synagogue resulting in 11 deaths.
November 7, 2018	Thousand Oaks, CA	Mass shooting at Borderline Bar & Grill resulting in 12 deaths.
May 31, 2019	Virginia Beach, VA	Mass shooting at a municipal building resulting in 12 deaths.
August 3, 2019	El Paso, TX	Mass shooting at a Walmart resulting in 23 deaths.

Table B2: Summary statistics for fire-level variables

Variable	Mean	Std. Dev.	Median	Max.
LAT Retardant Drops	16.51	29.76	5	252
Count of Airplane-Days	4.16	6.28	2	47
Any LAT suppression?	0.63	0.48	1	1
Total suppression expenditures	5632.78	16474.41	1000	182584.57
Max. Online Media Attention (statewide)	0.13	0.22	0.05	1.72
Any national TV story about state's fires	0.12	0.21	0	1
Fire burned during mass shooting	0.04	0.15	0	1
Fire burned during "media distraction"	0.08	0.19	0	1
Duration of wildfire (days)	15.52	14.23	13	116
Number of fires	265			

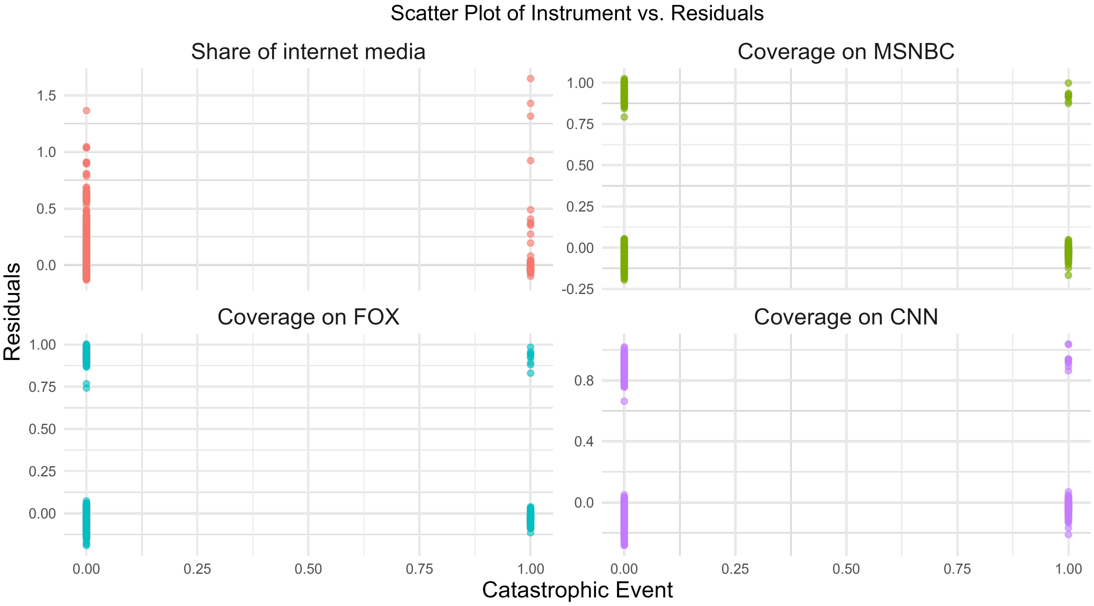

Figure B1: Residuals from the second stage regression regressed on the occurrence of catastrophic events

C Supplementary Materials for Chapter 4

Table C1: Heterogeneity of LAT suppression effectiveness by terrain ruggedness (TRI)

	(1) Burned cell?	(2) Burn Severity	(3) Time until burn
Drop Treatment * TRI	-0.004***	-0.001***	-0.036***
	(0)	(0)	(0.003)
TRI	-0.112***	-0.439***	-1.546***
	(0)	(0.001)	(0.006)
Drop Treatment	-0.037***	-0.055***	0.048***
	(0)	(0.001)	(0.011)
Controls?	Yes	Yes	Yes
Selection Algorithm #1	Yes	Yes	Yes
Selection Algorithm #2	Yes	Yes	Yes
Observations	9058	9058	3102

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

C1 Subset of drops orthogonal to wind

Table C2: Heterogeneity of LAT suppression effectiveness by count of overlaps

	(1) Burned cell?	(2) Burn Severity	(3) Time until burn
Drop Treatment * Drop Overlaps	0.001***	0	5.064***
	(0.000)	(0.000)	(0.096)
Drop Overlaps	0***	-0.002***	5.616***
	(0.000)	(0.000)	(0.072)
Drop Treatment	-0.05***	-0.059***	1.152***
	(0.000)	(0.001)	(0.168)
Controls?	Yes	Yes	Yes
Selection Algorithm #1	Yes	Yes	Yes
Selection Algorithm #2	Yes	Yes	Yes
Observations	9057	9057	3100
Dep. Var Mean	0.59	1.32	49.2

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

Table C3: Dependent Variable - Binary indicator of a cell burning after a drop

	(1)	(2)	(3)	(4)
Drop Treatment	-0.05***	-0.055***	-0.063***	-0.066***
	(0.000)	(0.000)	(0.000)	(0.000)
Fuels (1 - 12)		1.488***	1.674***	1.643***
		(0.007)	(0.007)	(0.008)
Slope		0.005***	0.004***	0.004***
		(0.000)	(0.000)	(0.000)
Burn Probability		-1.954***	-1.433***	-1.708***
		(0.024)	(0.024)	(0.027)
Temperature (C)		0.009***	0.009***	0.009***
		(0.000)	(0.000)	(0.000)
Wind Speed (m/s)		0.02***	0.021***	0.02***
		(0.000)	(0.000)	(0.000)
Wind Direction (degrees)		0***	0***	0***
		(0.000)	(0.000)	(0.000)
PDSI		-0.007***	-0.008***	-0.008***
		(0.000)	(0.000)	(0.000)
Elevation		0.001***	0.005***	0.005***
		(0.000)	(0.000)	(0.000)
Terrain (m)		-0.099***	-0.113***	-0.111***
		(0.001)	(0.001)	(0.001)
WHP (1 - 5)		0.023***	0.019***	0.02***
		(0.000)	(0.000)	(0.000)
Controls?	No	Yes	Yes	Yes
Selection Algorithm #1	No	No	Yes	Yes
Selection Algorithm #2	No	No	No	Yes
Observations	2612	2611	2536	2546
Dep. Var Mean	0.65	0.65	0.65	0.65

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

Table C4: Dependent Variable - MTBS Burn Severity measured post-fire

	(1)	(2)	(3)	(4)
Drop Treatment	-0.07***	-0.08***	-0.1***	-0.11***
	(0.000)	(0.000)	(0.000)	(0.000)
Fuels (1 - 12)		-5.73***	-4.62***	6.5***
		(0.06)	(0.06)	(0.02)
Slope		0.04***	0.03***	0.03***
		(0.000)	(0.000)	(0.000)
Burn Probability		-5.73***	-4.62***	-5.16***
		(0.06)	(0.06)	(0.07)
Temperature (C)		0.02***	0.02***	0.02***
		(0.000)	(0.000)	(0.000)
Wind Speed (m/s)		0.05***	0.05***	0.05***
		(0.000)	(0.000)	(0.000)
Wind Direction (degrees)		0***	0***	0***
		(0.000)	(0.000)	(0.000)
PDSI		-0.02***	-0.02***	-0.02***
		(0.000)	(0.000)	(0.000)
Elevation		0.09***	0.11***	0.1***
		(0.000)	(0.000)	(0.000)
Terrain (m)		-0.43***	-0.48***	-0.47***
		(0.000)	(0.000)	(0.000)
WHP (1 - 5)		0.09***	0.08***	0.08***
		(0.000)	(0.000)	(0.000)
Controls?	No	Yes	Yes	Yes
Selection Algorithm #1	No	No	Yes	Yes
Selection Algorithm #2	No	No	No	Yes
Observations	2612	2611	2536	2546
Dep. Var Mean	1.40	1.40	1.40	1.40

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.

Table C5: Dependent Variable - Time until burn (hours)

	(1)	(2)	(3)	(4)
Drop Treatment	3.60***	1.20***	4.56***	3.36***
	(0.24)	(0.24)	(0.24)	(0.24)
Fuels (1 - 12)		1288.56***	1016.64***	338.16***
		(11.28)	(13.92)	(2.64)
Slope		6.00***	6.00***	5.76***
		(0.000)	(0.000)	(0.000)
Burn Probability		1288.56***	1016.64***	1102.32***
		(11.28)	(13.92)	(14.40)
Temperature (C)		-3.36***	-3.36***	-3.36***
		(0.000)	(0.000)	(0.000)
Wind Speed (m/s)		-20.64***	-20.88***	-20.40***
		(0.000)	(0.000)	(0.000)
Wind Direction (degrees)		0***	0***	0***
		(0.000)	(0.000)	(0.000)
PDSI		-1.92***	-2.16***	-1.92***
		(0.000)	(0.000)	(0.000)
Elevation		3.84***	2.64***	2.64***
		(0.000)	(0.24)	(0.000)
Terrain (m)		-25.20***	-22.80***	-25.20***
		(0.24)	(0.24)	(0.24)
WHP (1 - 5)		0.72***	0.24***	0.48***
		(0.000)	(0.000)	(0.000)
Controls?	No	Yes	Yes	Yes
Selection Algorithm #1	No	No	Yes	Yes
Selection Algorithm #2	No	No	No	Yes
Observations	990	990	962	970
Dep. Var Mean	42.8	42.8	42.8	42.8

- Bootstrapped standard errors in parentheses.
- Sample built from randomly selected drops, then four randomly selected cells (one per treatment group).
- Selection algorithm #1: Pre- and post-drop observations selected based on common distance to drop.
- Selection algorithm #2: Pre-drop treatment and control points selected based on common distance to drop.