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Olli-Pekka Kuusela

This dissertation studies the microeconomics of forest fire suppression programs. It starts with an inquiry into the causes of increasing shares of public land management budgets devoted to wildland fire suppression in lieu of hazardous fuel reduction or other pre-fire risk mitigation programs. The first two chapters consider competing economic theories for why annual appropriations are predominantly devoted to suppression. The first chapter proposes that this unbalanced allocation can arise from a cost externality generated by the availability of reserve or supplemental funds for suppression. The second chapter proposes an alternative explanation: this type of skewed allocation can result from an incident manager's aversion to risk. Both chapters rely on a subgame perfect Nash equilibrium result to characterize the resulting budget allocation.

The third chapter also solves a subgame perfect Nash equilibrium to investigate the properties of the fire budgeting problem at the state government level where fire protection programs are funded in part through forest-based taxation. In this chapter, a state tax planner is restricted to two forms of taxation currently used to raise revenue for public forest fire protection programs: 1) a per-acre fee on forestland, and 2) a tax levied per-unit volume of timber

harvested. The model shows that when revenues for carbon storage can be captured by private forestland owners, then per-acre fees are the preferred instrument for raising tax revenues and result in a first-best equilibrium outcome. If instead carbon sequestration revenues are not captured by forestland owners, tax planners are constrained to a second-best equilibrium and the use of harvest taxes instead of the per-acre fee on land.

The fourth chapter applies a discrete choice econometric model to administrative data obtained from state and federal fire management agencies overseeing wildfires in the western United States from 2005 to 2014. The model investigates if changes in the availability of reserve funding earmarked for suppression had a significant impact on an incident manager's likelihood of adopting a full suppression response to unplanned wildfire. This chapter focuses on a change in federal budgeting and policy guidance occurring in fiscal year 2010 to determine if socioeconomic and climatic factors had a different effect on manager choices than they did prior to this policy change. A key factor measured to influence choices via the cost of risk is the distance that a fire burns from residential areas. The model estimates that this factor raised the probability of adopting full suppression following the policy change on fires managed in Washington but lowered the probability on fires managed in Oregon. The model finds evidence that the change in the availability of suppression reserve funds beginning in fiscal year 2010 negatively influenced the probability of adopting full suppression by a small margin, but the effects of this change are indistinguishable from the effects of an update to policy guidance released in 2009.

A Microeconomic Analysis of Wildfire Suppression Programs in the Western United States

by

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APPROVED:

Major Professor, representing Applied Economics

Head of the Department of Applied Economics

Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

David J. Rossi, Author

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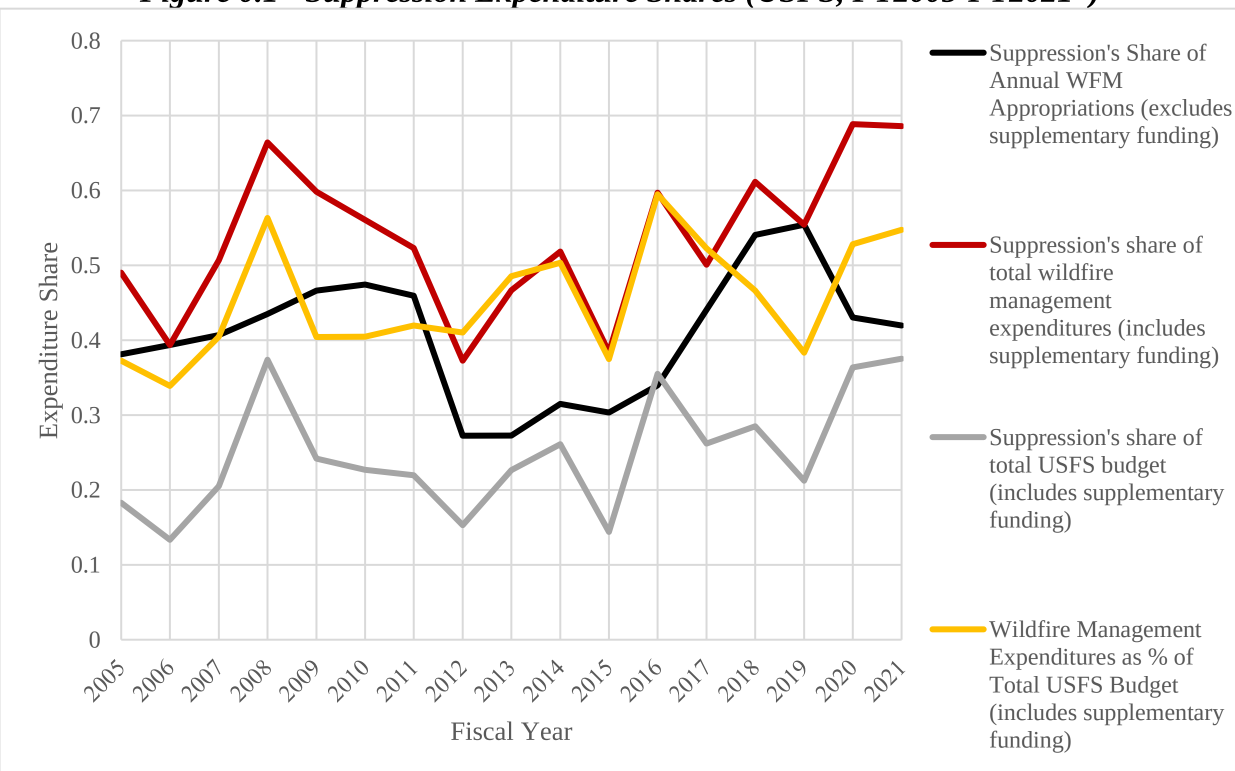
GENERAL INTRODUCTION

Wildfire suppression programs have become an increasingly visible source of costs for public land management agencies in the United States since the mid-1980s as acres, damages, and public expenditures on suppression are increasing (Lueck and Yoder, 2013). While climatic factors contribute to increasing fire severity (van Mantgem et al., 2013), they are not the only driver of these trends. Land management practices and patterns of land use change are critical considerations for understanding the patterns of fire behavior and risk in the western United States (Pyne et al., 1997). Throughout the 20th century, land management agencies adopted and refined a model of centralized command over suppression resource allocation in the United States (Lueck and Yoder, 2013, Lueck, 2012). Historically, aggressive suppression programs were developed to protect the nation's timber supply from wildfire damage, but as urban and residential land uses have expanded, public suppression programs have also benefited residential landowners adjacent to fire-prone forestland. These programs were initially developed in the early 20th century in lieu of vegetation management programs. While agencies began to experiment with vegetation management through the re-introduction of fire in the mid-1970s to mid-1980s (and more recently with the passage of the 2001 Federal Wildland Fire Management Policy), the full re-introduction and restoration of fire-dependent forests has been slow to develop.

Despite a now widespread recognition for the need to re-introduce fire on the landscape (Pyne et al., 1997), wildfire suppression still dominates federal and state fire management activities. Figure 0.1 shows several trends regarding budget shares in the U.S. Forest Service (USFS). First, wildfire suppression expenditures (including supplemental appropriations) have taken up an increasingly larger share of total USFS budget outlays (from 18.3% in 2005 to 37.5% (projected) in 2021). Second, the proportion of annual fire management appropriations

("WFM") devoted to wildfire suppression is consistently around 42%, but when supplemental appropriations are included, this share has displayed an annual average increase of 2.1% per year since 2005. All wildfire management programs now exceed 50% of annual USFS expenditures. The primary concern with rising shares of budgets devoted to suppression is the "fire paradox" (Thompson et al., 2013; 2018; Calkin et al., 2015), whereby the exclusion of wildfire from western U.S. forests can allow hazardous fuels to accumulate, leading to larger fires and exacerbating the need for future suppression effort. A positive feedback loop between suppression and large fire risk is preventing land managers and policymakers from getting ahead of the problem.

Figure 0.1 - Suppression Expenditure Shares (USFS, FY2005-FY2021*)



****2021 figures anticipated based on USFS budget proposal, USFS (2020).***

Government oversight agencies have recently recommended greater federal and non-federal agency cooperation in distributing risk-reducing fire management budgets and resources

(GAO, 2015). These resources may not be allocated efficiently due to coordination problems across political boundaries and across federal and non-federal agencies (Lueck, 2012; Moynihan, 2009). As I explore in this dissertation, there is potential for budgetary institutions to vary across federal and state fire management programs, and for objectives to differ across managers within a fire management organization or across federal, state, and private land managers. Increasing coordination across these actors requires a better understanding of the sources for these differing objectives and what role funding institutions can have on equilibrium outcomes.

One important budgetary institution that drives fire suppression decisions is the funding mechanism for emergency forest fire suppression operations. Beginning in 1908, the U.S. Congress approved off-budget financing for emergency wildfire suppression, giving the U.S. Forest Service an effective “blank check” to fight forest fires (O’Toole, 2007). These federal expenditures are not subject to regular appropriations rules and are therefore not subject to budget caps or sequestrations, nor are these expenditures counted toward estimates of the federal deficit despite contributing to an increase in federal interest expenses on the debt. This practice continued from 1911 to 1978.

The practice of off-budget financing for fire suppression was phased out in 1978 at the request of the Office of Management and Budget (O’Toole, 2007). From 1978 to 1986, federal agencies began experimenting with less aggressive fire suppression policies (particularly within the National Parks Service) to avoid exceeding annual budget allotments and to restore fire-deprived ecosystems. However, two severe fire seasons in 1987 and 1988 led congress to allow the Forest Service to borrow funds from non-fire accounts in order to finance their fire suppression efforts. In 1990, congress set up a “contingency fund”, which can be utilized with presidential approval. This fund created an annually appropriated reserve account that can be accessed only when annual appropriations have been exhausted, but its use had phased out by 2004 (GAO, 2004). A similar set of accounts was formally re-established in fiscal year 2010, following the passage of the Federal Land Assistance, Management, and Enhancement (FLAME) Act, but were phased out by fiscal year 2018. This approach for funding wildfire suppression response at the federal level is unlike the approach taken by state forestry agencies such as CALFIRE and the Oregon Department of Forestry, which rely more heavily on tax receipts for funding state-level fire management responsibilities. In either case, the capacity to engage in off-budget financing beyond annual appropriations and annually funded reserve accounts remains intact. In 5 of the 10 years from 2008 to 2017, off-budget supplemental or emergency suppression funds were granted to the U.S. Forest Service and the Department of Interior agencies beyond annually appropriated funds (Hoover and Lindsay, 2017).

Aside from the pressures of drier and hotter climates in the American west, there are several competing economic theories for why land management agencies continue to rely heavily on suppression efforts as a means for reducing fire risk, in lieu of pre-fire risk mitigation efforts like hazardous fuel reduction. The first explanation interprets the demand for suppression as a direct result of reserve or supplemental funding institutions, which have enabled land management agencies to shift a portion of the costs of suppression onto other agencies or the general public via off-budget financing or the creation of annual reserve accounts (Donovan and Brown, 2005; Donovan et al., 2008; Rossi and Kuusela, 2019). The full costs of suppression are not budgeted for by land management agencies and other entities are left to bear the cost. This view effectively treats the cost of suppression as a negative externality generated by incident managers employed or contracted by land management agencies, not unlike a polluting factory which fails to internalize the full social costs of its emissions.

A second explanation borrows from the behavioral economics literature (Maguire and Albright, 2005; Wilson et al., 2011; Thompson, 2014). This view recognizes the considerable complexity involved in incident management decision-making, and the limited ability for even highly-trained professionals to compile, organize, and continually update their understanding of costs or risk. Managers must gather and effectively utilize large quantities of information about future fire risk and ongoing fire spread. This view is perhaps stated best by Herbert Simon in his 1947 book "*Administrative Behavior*", where Simon outlined a competing theory to rational decision-making in his theory of "satisficing" behavior:

> "*To achieve a completely successful application of a city's fire protection problem, the members of the fire department would need to know in comprehensive detail the probabilities of fire in each portion of the city- in fact, in each structure- and the exact effect upon fire losses of any change in administrative procedure or re-distribution of the fire-fighting forces.*"

Indeed, this acknowledgement of incomplete rationality (exemplified by limits on a fire manager's knowledge during a time-pressured decision environments), is what has led to a growing body of research which attempts to find satisfactory solutions (rather than globally optimal solutions), to this problem of efficiently allocating suppression resources not just across a city or a single landscape (Wei et al., 2019), but across the entire western United States (Wei, et al., 2020). Under this behavioral view, the sheer complexity of the suppression resource allocation problem is what has prevented managers from making efficient allocation decisions and is why operations researchers employ the use of heuristic decision algorithms to approximate the best feasible allocation. Additionally, the need for simpler decision heuristics which provide quick information about suppression effectiveness per-unit cost is one method for overcoming these sorts of information problems at the operational scale (Stonesifer et al., 2017). The reliance on heuristics in both managerial and computational settings represents a departure from the rational calculus of "*homo economicus*."

A third explanation for agencies' continued reliance on suppression effort abandons the commonly cited behavioral interpretation and instead views incident managers as rational decision makers under uncertainty (e.g. Gollier, 2001). Wildfire suppression operations involve considerable risk and outcomes of suppression strategies are not known with perfect precision. Instead of assuming that incident managers do not know about this risk or do not have the tools necessary to compile this information, we can assume that managers do know the shape of the payoff distribution they face when allocating resources but may be averse to the uncertainty over the outcome (Rossi and Kuusela, 2020). A manager's tolerance for risk is potentially a unique characteristic of individual decision-makers which is unobservable and may vary across wildfire incident managers (Hand et al., 2017). Furthermore, incident managers may be averse to third-moment characteristics of the payoff distribution they face, which may serve to exacerbate their demand for suppression resources (Rossi and Kuusela, 2020).

A final economic interpretation relates to the complicated geography of the fire management environment. There is often a close proximity of fire-dependent forests to both residential areas and commercially managed timberlands. The fragmentation of land tenure over forested areas can considerably complicate the wildfire management problem and lead to externalities across land ownership boundaries (Lauer et al., 2017; 2019). Historically, land management agencies actively suppressed fire to protect valuable timber resources on both public and private land (Pyne et al., 1997), a practice which continues to benefit private timberland owners today. However, over the last 30 years, the American west has also seen a gradual expansion of residential land uses into forested areas which has complicated the wildfire management problem by increasing fire risk and suppression expenditures (Bayham and Yoder, 2020; Radeloff et al., 2018). In contrast to federal agencies, state agencies provide fire protection over areas with considerably greater heterogeneity of land tenure. For example, state agencies have fire protection jurisdiction over the "Oregon and California Railroad Revested Lands," which consists of a checkerboard pattern of private and public land. Fire protection programs at the state level are funded in part through residential property taxes or forest-based taxation. This may place added pressure on agencies to adopt an aggressive suppression response to protect private lands from which public revenues are drawn. Further, state land management agencies do not have the same institutional capacity in their organization to fund hazardous fuels management programs at the same scale as federal agencies are now capable of doing under current fire policy. Recent changes in how federal agencies manage unplanned events through "let-burn" policies may have the unintended consequence of leading state agencies to fight fire more aggressively within their jurisdiction, since fires may spread from federal land into private jurisdictions where state land management agencies are primarily responsible for providing fire protection services.

The purpose of this dissertation is to formalize and measure the effects of these competing theories of suppression demand through numerical microeconomic models and a data-driven econometric application. The following chapters of this dissertation are organized as follows. In Chapter 1, a theory of sequential fire management budget allocations is developed in a deterministic setting. This chapter considers the effect of budgetary institutions which permit a portion of suppression costs to fall on outside agencies. When federal fire management budgets are determined sequentially, this budgeting institution can generate an inefficient allocation of funds across suppression and presuppression programs at the national level. Essentially, the cost externality increases the share of annual fire management expenditures devoted to suppression. In the absence of this cost externality, the sequential budgeting institution poses no problems for the efficient allocation within the fire management organization. This chapter also considers the possibility for this cost externality to arise from "satisficing" behavior which places an unequal weight across competing objectives of the fire management program.

In chapter 2, I extend on the sequential formulation of the wildfire economics model to incorporate the effects of risk on the equilibrium budget allocation at a regional scale. In contrast to the institutional setting in chapter 1, this chapter assumes that the full costs of suppression are internalized during the suppression decision stage. However, this chapter finds a similar inefficiency of budgets arising from a representative incident manager's aversion to higher order characteristics of the net value change distribution. Similar to the result presented in chapter 1, risk aversion can drive an increase in the demand for suppression resources and an increase in the share of fire management expenditures spent on suppression programs.

In chapter 3, I focus on fire protection budgeting practices at the state level and consider how a portion of these protection expenditures are financed through forest-based taxation. This chapter assesses the relative advantages of two alternative taxation schemes that are used in the state of Oregon to raise funds for fire protection. This model considers how fire risk is endogenously determined by suppression effort afforded from forest-based taxes when a representative landowners internalizes and does not internalize the value of carbon storage. A key contribution of this chapter is to show that when carbon sequestration revenues can be captured by the landowner, an acre-based land value tax is preferred to a harvest tax as it minimizes deadweight loss.

In Chapter 4, a revealed preference model of incident managers is presented and applied to administrative data from federal and state land management agencies to test several hypotheses about the effects of socioeconomic factors that drive suppression decisions. The analysis is focused on the suppression choices of incident managers in California, Oregon, and Washington between fiscal years 2005 and 2014. The discrete choice models recognize that, in addition to climatic and weather factors, budgetary institutions and socioeconomic factors may drive a manager's decision to actively suppress an unplanned wildfire (see Donovan, 2005; Lueck and Yoder, 2013; Montgomery, 2014; Rossi and Kuusela, 2019; Rossi and Kuusela, 2020). Results from the choice models enable inferences about the effects of socioeconomic factors on suppression choices and a comparison of the magnitudes of these effects against those of weather or climate variables. I find that socioeconomic factors are statistically significant drivers of suppression choices; most notably the level of national demand for suppression resources and the distance between a fire's ignition point and nearby residential populations. However, dry monthly climatic conditions are measured to be more important factors for explaining choice variation across the sample. This chapter finds limited statistical evidence to suggest that an update to federal fire policy guidance during Fiscal Year 2009 had a distinguishable effect from the introduction of reserve funds in Fiscal Year 2010. If there was a positive impact of the reserve funds on the probability of selecting a full suppression strategy, it was outweighed by a negative impact from the 2009 policy guidance. This potential for counteracting effects may be why the expected probability of choosing full suppression fell by only a small margin after the introduction of the reserve funds. I focus on policy implications and directions for future research in the General Conclusions.

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CHAPTER 1: COST PLUS NET VALUE CHANGE (C+NVC) REVISITED: A SEQUENTIAL FORMULATION OF THE WILDFIRE ECONOMICS MODEL

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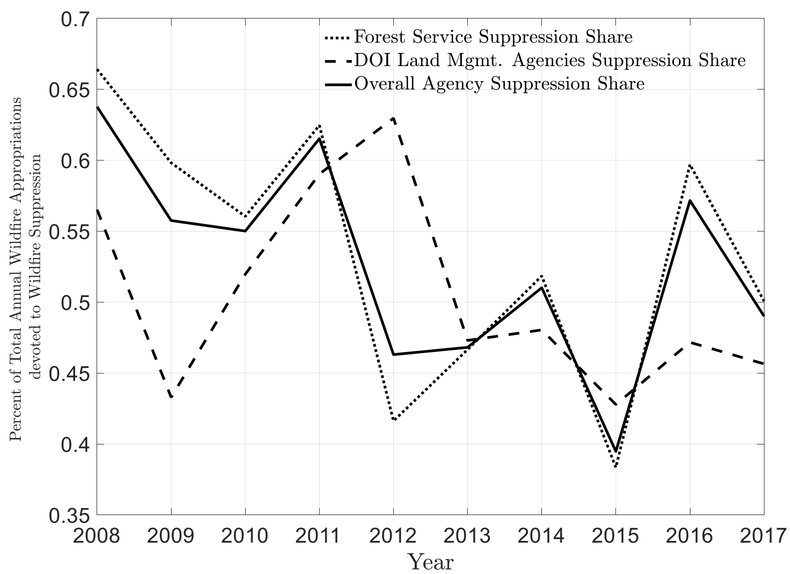
1.1. Introduction

Federal wildland fire expenditures in the United States have been rising alongside an increased frequency of large wildfires over the past half-century. Since 1985, the average size of wildfires has increased by an annual average of 3.95% per year, while federal suppression expenditures have increased by an annual average of 6.7% per year (NIFC, 2017). One consequence of this trend has been the shift of spending patterns within federal land management agencies toward fire management, and particularly toward wildfire suppression activities (Calkin et al., 2015; Hoover and Lindsay, 2017). A majority of annual USDA Forest Service expenditures are now devoted to fire management operations of one form or another, and suppression expenditures have encompassed over one-half of federal fire management costs in 6 of 10 years from 2008 to 2017 (see Figure 1.1). Such expenditure trends have raised severe concerns among policymakers and federal land managers, since increasing shares of annual budgets devoted to wildfire suppression hinder federal agencies' ability to invest in nonfire-related land management programs and to effectively mitigate the risk of future damages (Calkin et al., 2015; USFS, 2015; Ingalsbee, 2017).

The availability of supplemental financing for suppression has been identified as one of the key drivers of rising suppression costs and the consequent inefficiencies of federal fire management programs (Donovan and Brown, 2005). The inefficiencies arise when spending on suppression is determined reactively during the fire season rather than simultaneously alongside other fire management budgets, thus neglecting the interdependencies between program components (Agee et al., 2000; Hesseln, 2001; Hirsch et al., 2004; Mogghaddas and Craggs, 2007). Consequently, several studies stress the efficiencies provided by a unified framework in which supplementary funding is not available during suppression response (Rideout et al., 2008; Wei, 2012; Minas et al., 2015; Heines et al., 2018). However, while such studies are important in prescribing efficient policies, they do not adequately describe the spending decisions made in a realistic policy context. In fact, no prior studies in the fire economics literature have characterized the expenditure allocation arising within a fragmented (or "sequential") budgeting procedure, thus hindering efforts to understand the incentives behind program spending decisions. This becomes especially relevant when the objectives of the decision-makers across the fragmented process are not aligned.

Figure 1.1 - Federal Suppression Budget Share by Agency



Source: Hoover and Lindsay (2017)

Over the past three decades, the U.S. Government Accountability Office has published several rounds of recommendations with the goal of encouraging a better alignment of incentives within the fire management program and improving overall program efficiency through the increased development and use of decision support tools (GAO, 2015). However, despite an ample amount of decision-support information provided to incident commanders, the sheer complexity of a wildfire event often limits the efficiency gains from these tools (Calkin et al., 2013; Thompson, 2014; Dunn et al., 2017). Because of this complexity, incident commanders may display impatience and accept suboptimal solutions to their management problem when the time needed to search for the best solution is too long (Maguire and Albright, 2005; Wilson et al., 2011). This tendency to rely on heuristic solutions represents a form of satisficing and can be an important driver of forest management outcomes and wildfire management outcomes in particular (Taynor et al., 1990; Wilson et al., 2011; Holmes and Calkin, 2013; Valatin et al., 2016). This can impact long-term trends in fire management by limiting the time spent using decision support models to explore a complex decision space and yield more cost-effective suppression strategies and alternatives to conventionally aggressive response tactics (Thompson et al., 2017).

The purpose of this chapter is to analyze the implications of the fragmented budgeting process on federal fire program spending decisions when the objectives of decision-makers within the process is not aligned (either due to existing supplementary funding institutions or the complexity of suppression-stage decision-making). To that end, we develop a new theoretical model of organizational decision-making to determine the demand for fire management effort. This theoretical model presents the wildfire management problem within a game-theoretic structure whereby a public organization's presuppression and suppression demand decisions are made in sequence. A representative presuppression manager acts as a Stackelberg leader and a representative suppression manager as the follower. The advantage of this approach is an ability to assess potential deviations from the socially optimal allocation of fire management effort in the presence of fragmented budgeting.

We derive several new insights that contribute to the Cost Plus Net Value Change (C+NVC) literature. First, our model results highlight the fact that this fragmentation does not, on its own, generate any deviations from the socially optimal allocation. However, when the objective function in the suppression stage of the model is subject to a heuristic weighting scheme, fragmentation will generate an allocation that deviates from the socially optimal allocation. By "heuristic weighting," we mean the suppression manager's tendency to assign more importance to the goal of damage mitigation over the goal of suppression cost minimization (Calkin et al., 2013). We also show how changes in the heuristic weight can potentially lead to an inverse relationship between suppression and presuppression expenditures, even when the components of the fire program are technological and strategic complements. Our results enable policymakers and analysts to better understand the causes of inefficiencies in fire program spending and how changes in the availability of supplemental funding might, or might not, improve program efficiency.

The rest of this chapter is organized as follows. In the next section, we review the budgeting procedure for wildfire management in the United States and the standard fire economics model. In Section 3, we derive the solutions for the sequential model and compare these solutions to those of the standard model. Section 4 provides a numerical application of the model to explore its comparative statics and key results. Section 5 discusses the policy implications of the model's results and the potential for further modification of the sequential model. Section 6 concludes.

1.2. Review of Federal Wildfire Program Spending

Federal land management agencies in the United States seek to efficiently allocate funding between two composite components of the national fire program: (1) suppression effort (which includes initial attack, extended attack, and efforts to manage unplanned wildfires for resource benefits) and (2) presuppression (which refers to fuels management, wildfire preparedness, and fire prevention efforts). In the United States, funding for both suppression and presuppression operations are allocated through annually appropriated Wildfire Management accounts (WFM). The WFM accounts are distributed to the Forest Service and Department of Interior agencies' respective Offices of Wildland Fire and then distributed to regional landscape management programs (GAO, 2015). The WFM accounts are broken into two subaccounts: (1) fire operations (for preparedness and suppression efforts) and (2) other fire operations (intended for fuels management and other presuppression needs).

Regional distributions of WFM funds for presuppression efforts are based in part on past allocations and in part on landscape level budgeting models (GAO, 2015). These models provide the Office of Wildland Fire with some information about the expected return on fire management investment and generate strategic guidance for land managers as the analysis is prepared as part of a landscape's fire management plan. However, annual budget requests for covering suppression needs in the WFM accounts are based on a weighted moving average or prior program-wide expenditures (Abt et al., 2008). These suppression forecasts are void of information about how changing local conditions or presuppression expenditures can either increase or decrease the need for further suppression actions and have underestimated suppression expenditures in 8 of the 10 years between 2008 and 2017 (Hoover and Lindsay, 2017).

When appropriations from the fire operations subaccount have been spent, agencies can also utilize funding appropriated with the approval of Congress. Agencies are authorized to transfer funds from subaccounts (as well as from other non-fire accounts) to finance emergency suppression efforts when annual accounts are exhausted and additional appropriations are not granted.[1] A new funding rule, passed as part of a recent federal spending bill and which closely resembles the proposed Wildfire Disaster Funding Act (WDFA), now requires suppression appropriations to be determined based on the Fiscal Year 2015 moving average estimate plus an additional amount from a disaster cap adjustment. However, this additional funding request which utilizes funding from the disaster cap is also based on criteria independent from the determination of presuppression budget needs. Under the new funding rule and the WDFA, additional funding requests beyond the initial annual appropriations are available through the Disaster Relief Fund and must be approved by Congress.

In the event of an unplanned wildfire incident, fire management officers (at the unit, regional, or state level) must determine the initial scale and complexity of the incident based on established criteria and request additional funding for fires with higher severity or complexity than what can be managed with the available budget (NWCG, 2014). This classification of the incident's complexity serves as a guide to agency administrators who contract out suppression efforts to a Type 1 or Type 2 incident command team.[2] An incident commander then assumes control over extended attack efforts after an official transfer of authority is written and a complexity report is supplied by the fire management officer (NWCG, 2014; NNIFC, 2018). The ICT then attempts to meet the objectives and budgetary constraints of the landscape's fire management team (the agency administrator and fire management officer) but is not required to

[1] The FLAME fund has been eliminated for fiscal year 2018. In the absence of the FLAME fund, all supplemental appropriations will have to be granted by congress through alternative supplementary accounts available under the Wildfire Disaster Funding Act. These funds may be used to finance large fire suppression costs before or after the fire operations subaccount has been fully utilized.

[2] The wildfire incidents are designed based on their complexity on a scale from 1 to 5, with incident Type 1 referring to the most complex fires. Type 1 and Type 2 ICTs manage and organize hundreds to thousands of different resources (Hand et al., 2017).

satisfy these constraints by law or through a legally binding contract (NIFC, 2018). Furthermore, contracted ICTs face no financial penalty for exceeding these budgetary constraints and may recommend that fire management teams develop a new suppression strategy or approved course of action. While agency administrators must approve an ICT's request for additional funding during a Type 1 or Type 2 incident, there are few or no limits on the availability of supplemental suppression funding when also approved by Congress (Donovan and Brown, 2005; Lueck and Yodeer, 2015). An organization structured in this way lowers the effective marginal cost of suppression (Lueck, 2012) and introduces a tendency for incident commanders to overweight the benefits of damage mitigation relative to the costs of suppression (Calkin et al., 2013).

Early attempts to characterize the efficiency of fire management organizations date back to Sparhawk (1925). In Sparhawk's model, the optimal investment in precautionary management (i.e. pre-suppression) is determined where the marginal reduction in fire-related damages from such investment is equal to the marginal costs of the investment. Implicit in this formulation of the model is an assumption of dependency between the two components. Larger upfront investments are assumed to reduce future expenditures on suppression (at a decreasing rate) as the detrimental effects of wildfire are diminished through precautionary behavior.

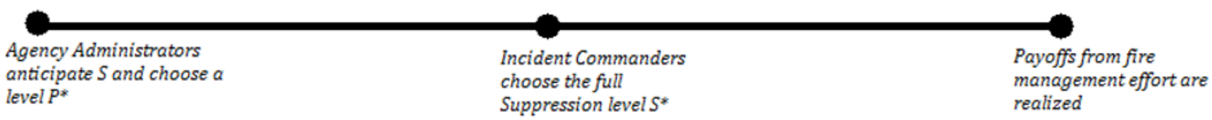
A key criticism of Sparhawk's model is that the restriction imposed by an assumed dependency between program components can make Pareto efficient allocations unattainable. The economic model presented by Donovan and Rideout (2003) shows that a negative dependency between pre-suppression and suppression can produce an allocation that diverges from a corrected social planner's problem where investments in pre-suppression and suppression are simultaneously chosen inputs. The corrected model shows that the Pareto efficient allocation of fire management budgets is obtained within a unified program where components of the program are related through the production function or joint cost function (Rideout et al., 2008).

Numerical applications of the unified framework at the landscape scale show significant gains in efficiency arising from a simultaneous determination of fuels management and investment in suppression capacity (Rideout et al., 2008; Wei 2012; Minas et al., 2015; Heines et al. 2018). These applications demonstrate how the complementary nature between suppression and pre-suppression investments justifies a unified budgeting framework. In these models, the investment in landscape-level fuel treatments enhances the marginal product of suppression by reducing the response times for initial attack resources. Minas et al. (2015) compared the results of an integrated scheduling model with "coordinated" and "independent" approaches to support this conclusion. However, the integrated simulations presented by Minas et al., (2015) assume perfect cooperation between fire administrators and the incident command teams (ICT), and the resulting pattern of fuel treatment is not sensitive to the ICT's capacity to exceed the suppression budget allotment in response to high severity events. This characterization of the budgeting scheme is not consistent with current budgeting practices within public fire management organizations in the U.S. which justifies an inquiry about optimal management behavior within a fragmented budgeting process with the availability of emergency funding.

1.3. Sequential C+NVC Model

Given the above observations, we extend the standard C+NVC model to incorporate the possibility of a fragmented budgeting process to generate deviations from the socially efficient solution. Fragmented budgeting implies a sequential decision process whereby the chronological determination of demand for fire management effort follows the timeline in Figure 1.2. The payoffs from the fire management program are captured by a net value change (NVC) function (Simard, 1976; Donovan and Rideout, 2003). The NVC function describes the level of net damages a landscape will experience after a fire event depending on the level of pre-suppression (P) and suppression (S) inputs employed to limit these damages. The NVC function is typically assumed to be strictly decreasing and convex in P and S. This assumption implies that fire management effort can reduce the damaging effects of wildfire but does so at a decreasing rate. An agency administrator managing a fire-prone landscape has achieved an optimal allocation of suppression and pre-suppression effort when the marginal social costs of each component are just equal to their marginal reduction in social damages (Donovan and Rideout, 2003).

Figure 1.2 - Timeline for full determination of presuppression and suppression budgets



Consider the role of the agency administrators who oversee the management of fire-prone landscapes. The agency administrators make a pre-suppression decision prior to the start of the fiscal year (see Figure 1.2). This occurs *before* incident command teams have control over the deployment of suppression resources as unplanned wildfires arise throughout the year. This chronology reflects the institutional realm where agency administrators must request annual funding for fuels management and preparedness programs. In this setting, pre-suppression demand is determined retroactively before the full suppression budget (including emergency funding) is allocated. Optimal management thus requires the administrator to anticipate the full level of annual suppression funding that will be demanded at the time their request for pre-suppression funding is made. In game theory terminology, the administrator acts as the

Stackelberg leader in this hierarchical game structure and the suppression manager as the follower.

1.3.1. Suppression Stage

In the first part of the backward induction procedure, the incident commander (i.e. the follower) chooses a level of suppression effort which minimizes the sum of net damages plus some weighted importance of controlling costs for the agency administrator.

$$\min_{S \geq 0} \ \theta W_S S + NVC(P, S) \tag{1}$$

Here $\theta \in (0,1]$ represents the relative importance of controlling cost relative to damages and W_S is a constant unit cost of suppression effort.[3] This heuristic specification (1) enables an interpretation of the demand for suppression as a satisfactory solution, rather than a fully rational solution to the first-stage problem. When $\theta = 1$, the ICT equally weights the competing goals to minimize costs and net damages. Notice that as $\theta \to 0$, the ICT places greater importance on the goal of mitigating fire damages relative to the competing goal of controlling suppression costs.

The ICT's choice of suppression effort is then determined by the necessary condition of (1):

$$\theta W_S = -\frac{\partial NVC(P, S)}{\partial S} \tag{2}$$

Rearranging condition (2) to solve for S yields the incident commander's best response function: $S(P, W_S, \theta)$. When the left-hand side of (2) is lower, the net gain from deploying suppression

---

[3] Suppose that $\theta(t) = \frac{t}{1+t}$ for some exogenous search time $t \in (0, \infty)$. In equation (1), this enables the term $\theta W_S S$ to be expressed in terms of search time: $\theta W_S = \frac{t W_S S}{1+t}$. As $t \to \infty$, the relative importance of minimizing costs increases at a decreasing rate. When less search time is permitted, the relative importance of minimizing costs decreases.

effort is larger from the ICT's perspective (fewer damages with less costs). Less than full consideration of the true costs of suppression ($\theta < 1$) raises the incident commander's demand for suppression relative to $\theta = 1$. In other words, suppression demand is decreasing in θ (see Proposition 1 below).[4]

To investigate the sign of the strategic relationship between S and P, we use the Implicit Function Theorem to derive the following result from equation (2):

$$\frac{\partial S(P, W_S, \theta)}{\partial P} = -\frac{\frac{\partial^2 NVC(P,S)}{\partial S \partial P}}{\frac{\partial^2 NVC(P,S)}{\partial S^2}} \tag{3}$$

Notice that a minimum solution to the incident commander's problem is attainable if $\frac{\partial^2 NVC(P,S)}{\partial S^2} > 0$. Hence, the sign of the numerator in (3) will determine the nature of the strategic relationship between the pre-suppression and suppression inputs. If the marginal effectiveness of suppression input is decreasing in pre-suppression effort (numerator is positive), the two inputs are strategic substitutes (expression (3) is negative).[5] If the opposite holds, the resources are strategic complements. In the next subsection, we show that the necessary and sufficient conditions for a global minimum in pre-suppression expenditures imply a complementary technological relationship between P and S. This suggests that the inputs are also strategic complements (expression (3) is positive). If complementarity holds, increasing applications of

[4] To be sure that $S(P, W_S, \theta)$ represents a valid best response in the context of the incident commander's objective, it must be true that $\frac{\partial^2 NVC(P,S)}{\partial S^2} > 0$. This inequality holds under the assumption of a convex fire management technology and enables the proof of Proposition 1 (see Appendix A).

5 Recall that $\frac{\partial NVC}{\partial S} < 0$ and $\frac{\partial NVC}{\partial P} < 0$. These partials mean that NVC is decreasing in the inputs. If the cross partial derivative is positive, then the marginal effectiveness of input use is decreasing.

pre-suppression effort will lead the incident commander to increase subsequent requests for suppression resources due to the increasing marginal product of suppression.[6]

1.3.2. Presuppression Stage

To understand the optimal management strategy in response to the satisficing incident commander, we maintain the assumption of a sequentially rational agency administrator. Under this assumption, the administrator accurately anticipates the future suppression strategy employed by the incident commander. Substituting the incident commander's best response function into the administrator's objective yields a restricted C+NVC function (4):

$$\min_{P \geq 0} W_P P + W_S S(P, W_S, \theta) + NVC\big(P, S(P, W_S, \theta)\big) \tag{4}$$

The similarity of (4) to Sparhawk's restricted model lies in the exogeneity of suppression effort and an assumed dependency between P and S. However, in this case, the administrator can indirectly influence the level of suppression through knowledge of the incident commander's best response, $S(P, W_S, \theta)$. As we will see in the next paragraph, when $\theta < 1$, the suppression manager's actions generate a negative externality problem from the perspective of the administrator.

The resulting first-order condition for the restricted model is then:

$$W_P + \frac{\partial S(P, W_S, \theta)}{\partial P}\left[W_S + \frac{\partial NVC(\cdot)}{\partial S}\right] = -\frac{\partial NVC(\cdot)}{\partial P} \tag{5}$$

Which is equivalent to

$$W_P + \frac{\partial S(P, W_S, \theta)}{\partial P}\left[W_S + \theta W_S - \theta W_S + \frac{\partial NVC(\cdot)}{\partial S}\right] = -\frac{\partial NVC(\cdot)}{\partial P} \tag{6}$$

[6] A recent empirical study found that fuel treatments can increase per-acre estimates of suppression costs on large fires, indicating that suppression is viewed by managers as safer and easier following presuppression efforts (Gonzales-Caban et al., 2017; Southern Fire Exchange, 2018).

Under the assumption of sequential rationality, the agency administrator correctly anticipates that condition (2) will hold. This allows a simplification of condition (6) to be expressed as:

$$W_P = -\frac{\partial NVC(\cdot)}{\partial P} - \frac{\partial S(P, W_S, \theta)}{\partial P}(1-\theta)W_S \qquad (7)$$

The left-hand side represents the marginal cost of pre-suppression expenditures, whereas the right-hand side represents the externality adjusted marginal benefits. The first term in the right-hand side is the marginal benefit from pre-suppression effort in terms of reduced damages from wildfires. The second term on the right-hand side can be interpreted as the marginal external cost imposed by the incident command team. Changes in the pre-suppression input can either reduce or magnify the externality effect, depending on the sign of the best response function.

Notice that in general when $\theta \neq 1$ the necessary condition in (7) differs from the social planner's necessary condition derived in detail by Donovan and Rideout (2003). In the standard C+NVC model, the technological complementarity between the two inputs guarantees the existence of a global minimum, in addition to the assumption of diminishing marginal returns to both inputs. Hence, we will also assume the presence of such complementarity. This implies that the best response of suppression effort is increasing in pre-suppression (so that equation (3) is positive). Consequently, our specification of equation (4) departs from Sparhawk's original assumption of a negative relationship between P and S.

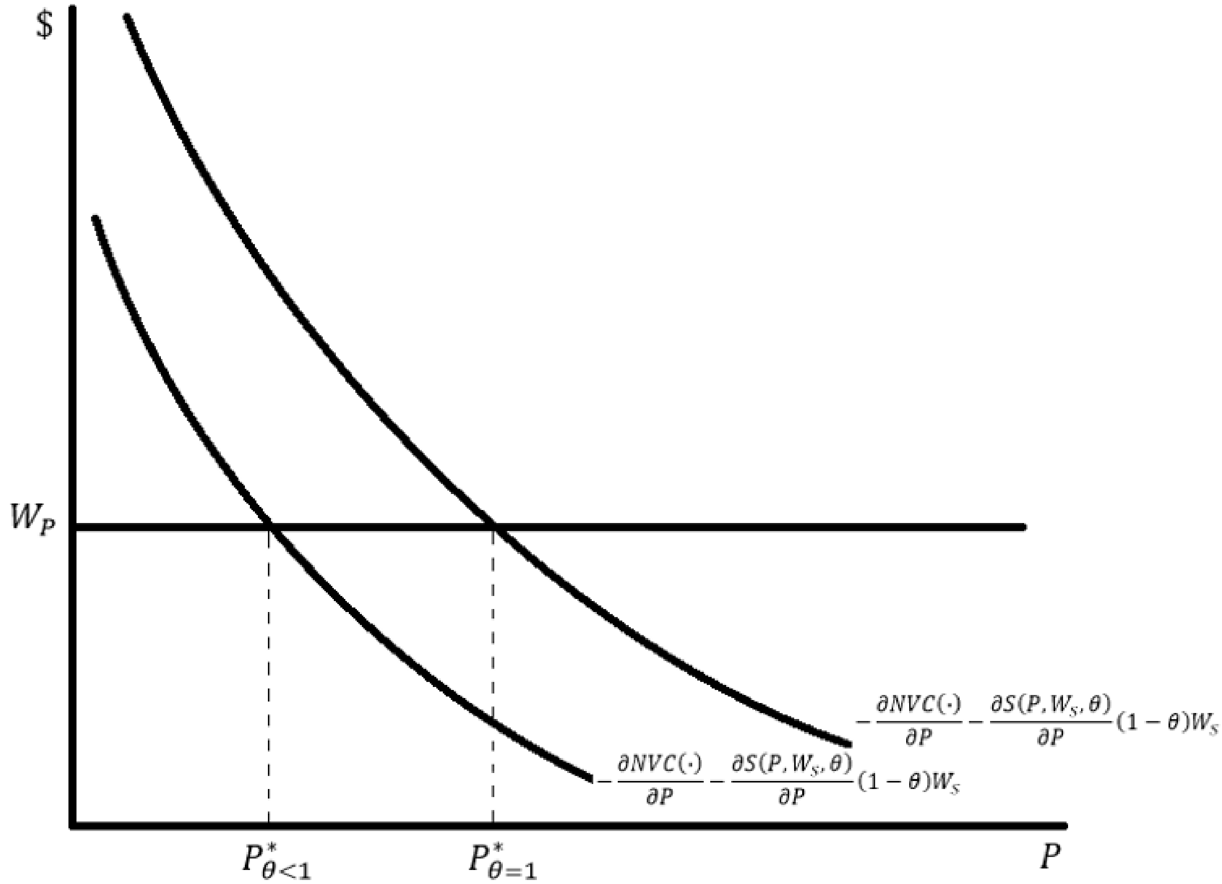
When the ICT places equal weight on the dual objectives to minimize costs and to minimize damages, we have $(1-\theta) = 0$. Such a situation corresponds to the standard C+NVC model. In this case, the full costs of suppression are accounted for in the restricted model (4) and the resulting first-order condition (7) collapses to condition (8).

$$W_P = -\frac{\partial NVC(\cdot)}{\partial P} \qquad (8)$$

The derived demand for pre-suppression is defined implicitly by equation (8) and expressed as a function of unit prices: $P^*(W_P, W_S)$. Using the implied expression for P^* to solve for the optimal level of suppression yields the incident commander's derived demand function: $S^*(W_P, W_S)$. Since the first order conditions, (2) and (8), are identical in this specification of the model as they are in the standard model, the resulting solution in the restricted model will yield an identical allocation to that derived in the unrestricted social planner's problem (derived by Donovan and Rideout, 2003). Consequently, the fire program's sequential C+NVC function will display the same properties and cross-partial effects as those derived for the social planner who solves (2) and (8) simultaneously for $P^*(W_P, W_S)$ and $S^*(W_P, W_S)$.

Suppose instead that the ICT placed a greater importance on the goal of minimizing damages. It should be clear that when $(1-\theta) > 0$, condition (7) does not collapse to the familiar optimality condition expressed in equation (8). The positive sign of (3) implies that the right-hand side of (7) is smaller than the right-hand side of (8) whenever $\theta < 1$, indicating that the marginal product of pre-suppression will be smaller when the ICT fails to fully internalize the full costs of suppression. This result implies that the fragmented budgeting structure produces an alternative allocation than that of the standard model by generating a larger demand for suppression effort, and a lower marginal social benefit from pre-suppression. The divergence of these outcomes is illustrated in Figure 1.3.

Figure 1.3 - Shifts in the Marginal Value Product of Presuppression effort under varying importance of suppression costs



As can be seen from Figure 1.3, changes in the parameter θ have an influence on pre-suppression expenditures in addition to suppression expenditures. A lower θ translates to higher suppression expenditures, but to lower pre-suppression expenditures. For example, if the value of θ has been decreasing, it is possible to observe a divergence in the pre-suppression and suppression expenditures as predicted by our model. This happens even when the two inputs are assumed to be technological complements. In fact, it is the strategic complementarity that generates such a pattern. We formally state this result in the following proposition:

<u>Proposition 1:</u> *Let the NVC function be of the Cobb-Douglas form and* $\theta \in (0,1]$. *Then strategic complementarity between components can create the following inverse relationship between suppression and presuppression whenever* $\frac{W_S S}{\beta P^{\gamma_1} S^{\gamma_2}} < 1 - \gamma_1$*:*

$$\frac{\partial S^*}{\partial \theta} < 0, \qquad \frac{\partial P^*}{\partial \theta} > 0$$

Alternatively, the following positive relationships hold whenever $\frac{W_S S}{\beta P^{\gamma_1} S^{\gamma_2}} > 1 - \gamma_1$*:*

$$\frac{\partial S^*}{\partial \theta} > 0, \qquad \frac{\partial P^*}{\partial \theta} > 0$$

<u>*Proof*</u>*:* See Appendix A.

Intuitively, Proposition 1 means that as incident command teams put more emphasis on the net value change component of the objective function, we observe a reduction in the pre-suppression expenditures and an increase in the suppression expenditures. This pattern is explained by the administrator's attempt to reduce the externality effect arising whenever $\theta < 1$ by reducing the organization's expenditures on pre-suppression. By doing this, the administrator is effectively mitigating the amount of inefficient spending on suppression.

To be sure that the solution implied by (7) (when $\theta \neq 1$) is indeed feasible, the second-order sufficiency condition requires the following relationship:

$$\text{SOSC} = \frac{\partial^2 NVC(\cdot)}{\partial P^2} + \frac{\partial^2 NVC(\cdot)}{\partial P \partial S}\left(\frac{\partial S(P, W_S, \theta)}{\partial P}\right) + \frac{\partial S^2(P, W_S, \theta)}{\partial P^2}(1-\theta)W_S > 0 \qquad (9)$$

If (9) is indeed positive, then it can be shown that the restricted objective function arising from a fragmented budgeting process, such as that expressed in equation (4), will yield a minimum solution. However, we can be sure that such a solution $(P^*_{\theta<1})$ will not necessarily be Pareto optimal since it does not coincide with the solution of a fully informed social planner who seeks an optimal budget for the fire program $(P^*_{\theta=1})$. Alternatively, if the inequality in equation (9) does not hold, then the restricted objective function arising from the fragmented budgeting process does not yield a minimum solution.

1.4. A Numerical Representation of the Sequential C+NVC Model

To investigate the feasibility of a minimum solution in this restricted case, consider the case of a Cobb-Douglas fire management technology with a convex functional form given by:

$$NVC(P,S) = \alpha - \beta P^{\gamma_1} S^{\gamma_2}$$

Where $(\alpha, \beta) \gg 0, \theta \in (0,1]$, and $0 < \gamma_i < 1$. The first-stage solution for the incident commander's problem is a best response function:

$$\left(\frac{\theta W_S}{\beta \gamma_2 P^{\gamma_1}}\right)^{\frac{1}{\gamma_2 - 1}} = \operatorname{argmin}_S\{\theta W_S S + \alpha - \beta P^{\gamma_1} S^{\gamma_2}\} \tag{10}$$

Equation (10) is a special case of the solution implied by equation (2). This function also enables a special case of equation (7), the agency administrator's restricted objective function:

$$\min_{P \geq 0} W_P P + W_S \left(\frac{\theta W_S}{\beta \gamma_2 P^{\gamma_1}}\right)^{\frac{1}{\gamma_2 - 1}} + \alpha - \beta P^{\gamma_1} \left(\frac{\theta W_S}{\beta \gamma_2 P^{\gamma_1}}\right)^{\frac{\gamma_2}{\gamma_2 - 1}} \tag{11}$$

As discussed in the previous section, the second order condition (9) has to be satisfied to guarantee the existence of a global minimum in (11). We examine the second order condition in more detail in Appendix B. In our simulations, we assume that the condition holds.[7]

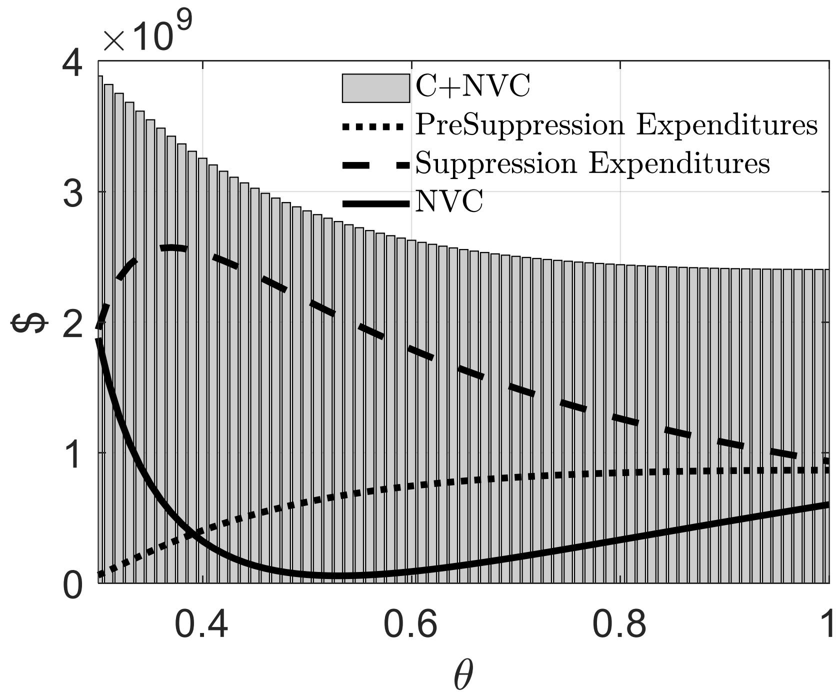
[7] Parameters used in the simulation reflect allocations at the national scale: $W_P = 500\ million, W_S = 600\ million, \alpha = 4\ billion, \beta = 2.5\ million, \gamma_1 = 0.255, \gamma_2 = 0.275$.

In Figures 1.4 and 1.5, we show the effect of the parameter θ on suppression and pre-suppression expenditures, on the net value change outcome, and on the overall program objective C+NVC. The latter is defined as:

$$W_P P^*(W_P, W_S, \theta) + W_S S^*(W_S, \theta) + NVC\big(P^*(W_P, W_S, \theta), S^*(W_S, \theta)\big)$$

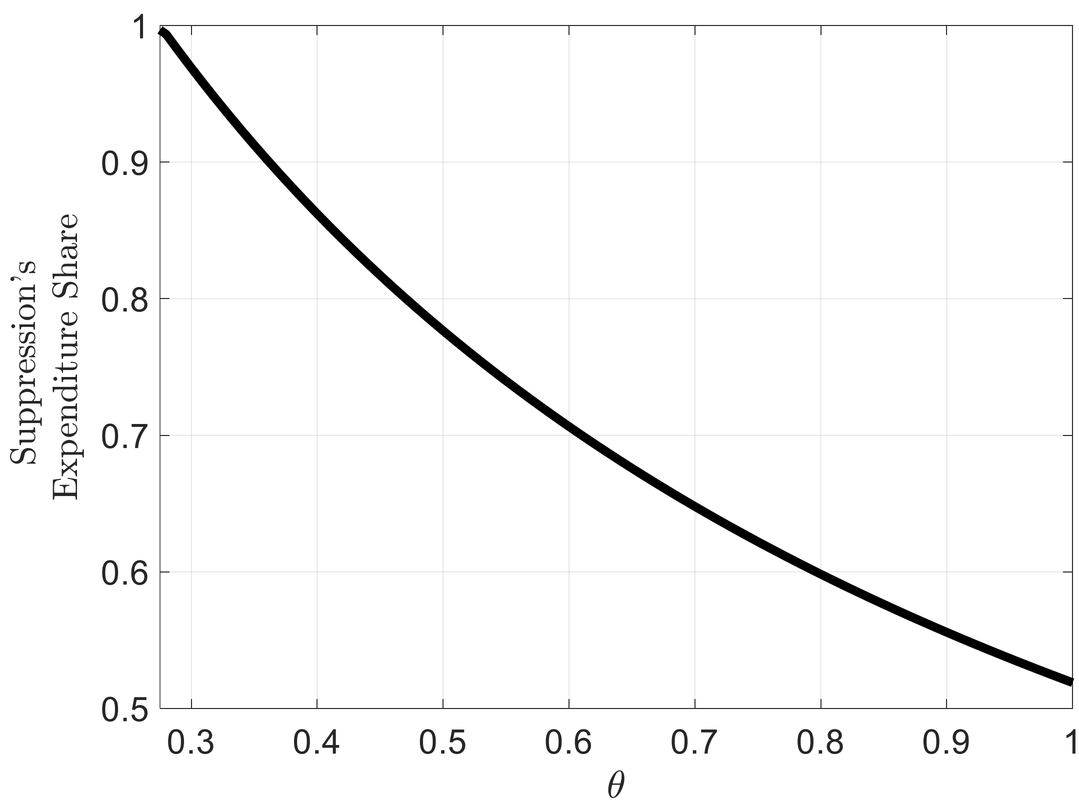
As to be expected, the C+NVC objective is minimized when $\theta = 1$. When $\theta < 1$, the total program costs are always higher. The dotted curve in Figure 4 shows the expenditures on suppression as a function of θ, and the dashed curve shows the expenditures on pre-suppression. As can be seen from Figure 1.4, the most balanced allocation of program expenditures occurs where $\theta = 1$. However, a decreasing θ translates to increasing suppression expenditures and to decreasing presuppression expenditures. There is a point, however, when the pre-suppression expenditures become so small that the suppression expenditures collapse as well. Figure 5 shows the suppression expenditures as a share of the total fire management expenditures. A greater share of the overall fire budget is allocated to suppression when the value of θ decreases.

Figure 1.4 - Total Program Costs and Net Damages



Unequal weighting of the dual objectives in the ICT's second stage problem yields inefficiencies in the fire program by altering the Pareto optimal budget share on suppression. Since agency administrators can indirectly influence the demand for suppression with their choice of pre-suppression effort, optimal management requires that they cut back their demand for pre-suppression due to the anticipated increase in suppression expenditures whenever $\theta < 1$. Administrators are less willing to invest in pre-suppression effort when contracted incident commanders fail to internalize the full costs of suppression effort. Thus, the demand for fire management effort in the presence of this externality yields a constrained Pareto allocation of fire management budgets and the relative share of overall program expenditures devoted to suppression increases.

Figure 1.5 - Suppression expenditures as a share of total program costs



It can be shown that the optimal level of pre-suppression effort occurs where the first-order condition of (11) is satisfied. Figures 1.6 and 1.7 illustrate more detailed properties of the sequential solution with the Cobb-Douglas specification. The Cobb-Douglas specification can be further explored to characterize the cross-price relationship. If the agency administrator faces a restricted objective function, as in (11), but the incident commander considers suppression costs to be an acceptable amount less than the true costs, ($\theta < 1$), then the cross-price relationship will be negative and the components will display complementarity (as in the Social Planner's case). Figure 1.6 (top) shows this negative cross-price relationship for both the social planner's problem and the Stackelberg case where the agency administrator maintains sequential rationality. Both cross-price relationships are negative over all unit costs of suppression but the Stackelberg case yields lower pre-suppression effort. An important result of this special case of the restricted model is its support for Proposition 1: the optimal level of pre-suppression effort increases as the ICT's perception about the relative importance of mitigating damages decreases $\left(\frac{\partial P^*}{\partial \theta} > 0\right)$. With more equal weighting between the incident commander's dual objectives, the optimal solutions converge towards those of the Pareto optimal outcome derived in the social planner's problem. Figure 1.7 provides an illustration of the strategic relationship between components under the sequential game and the social planner's problem.

Figure 1.6 - Demand for P and S under varying Importance of Suppression Costs

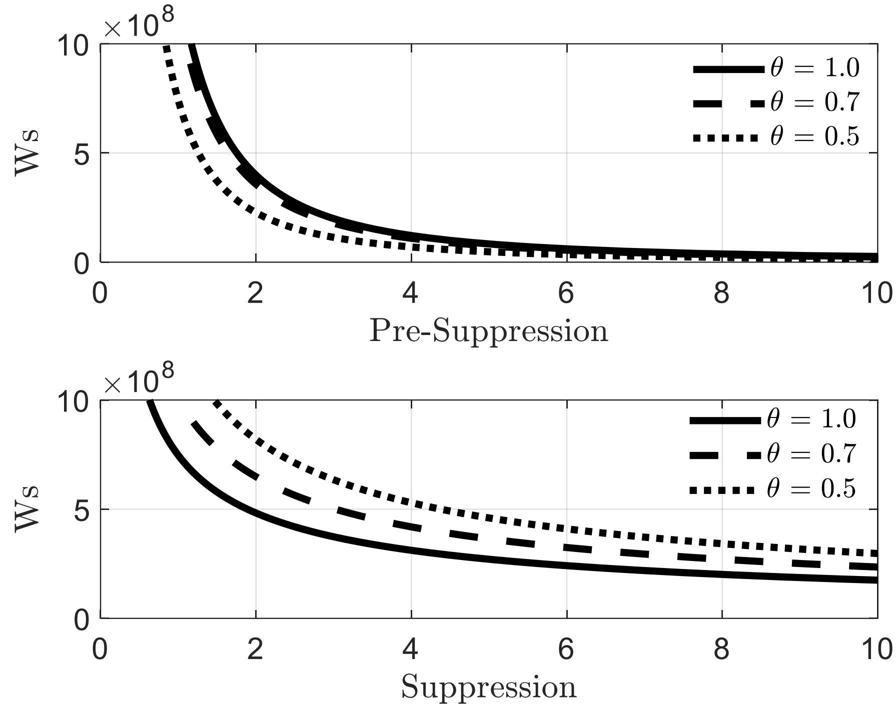
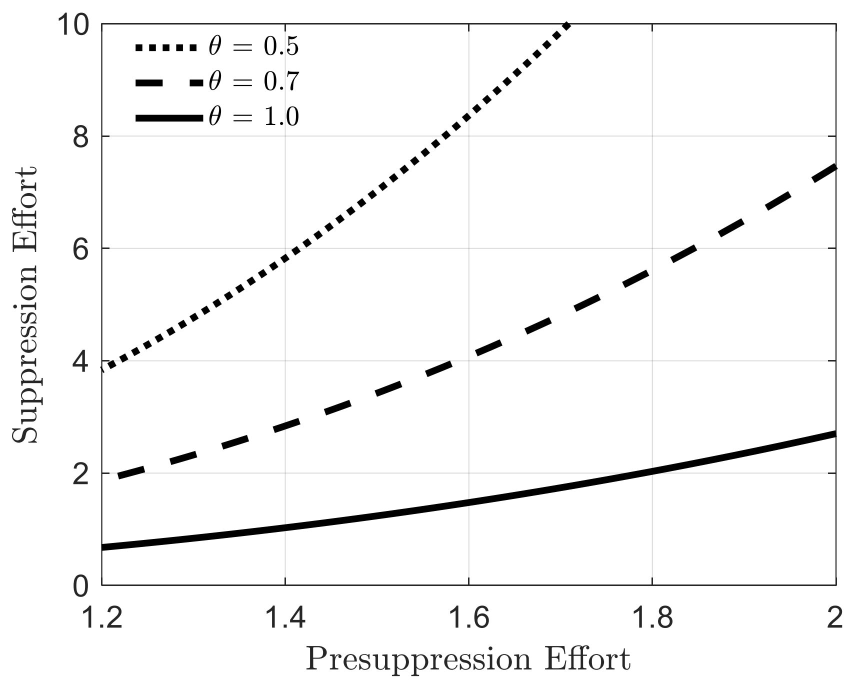


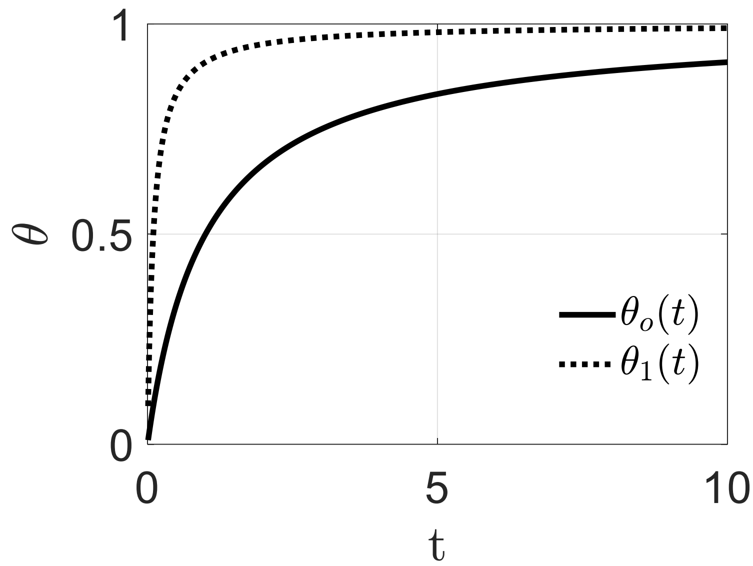
Figure 1.7 - Best Response relationship in the Sequential Game under varying importance of minimizing suppression costs



1.5. Discussion

This paper has shown that the heuristic weighting of the incident commander's dual objective function can impose a negative externality on agency administrators who seek to find the optimal demand for pre-suppression effort. The presence of this externality can negatively affect the overall efficiency of a wildfire management program. Possibility for such behavior during the suppression stage of the fragmented budgeting process means that incident command teams may put more emphasis on the value change (damage) component of the dual objective function in the C+NVC problem (Calkin et al. 2013). The tendency to overweight the importance of damage mitigation goals relative to cost minimization goals may reflect a type of heuristic search problem giving rise to "satisficing" behavior (Simon, 1987; Radner, 1975). Satisficing refers to an agent's acceptance of a near-optimal or sub-optimal solution to a complex optimization problem when the added cost of searching for better alternatives outweighs the benefits (Simon, 1955; Stigler, 1961). Notice the shift in Figure 1.8 from an initial heuristic weight θ_0 to a new larger weight θ_1. This shift is associated with an improvement in decision technology. The introduction of a better decision heuristic can enable the ICT to incorporate more costs under any given length of cognitive or computational search time, t.

Figure 1.8 - Importance of Suppression Costs as a Function of Exogenous Search Time



The simple static model presented above captures many of the key features of a heuristic search problem by abstracting from the complexity of a hyper-dimensional suppression decision problem and applying a heuristic weight to the ICT's dual objective function. The heuristic weight is shown to have the potential to generate a deviation from the Pareto efficient outcome when ICT's display impatience for finding the most cost-effective solution. The weighting parameter θ is specified to rise as the ICT's trial and error process progresses, providing the incident commander with a full consideration of suppression costs when $\theta = 1$. This trial and error process can be cut short due to an availability of supplementary funding or the influence of public pressures that force incident managers to adapt a swift suppression response and ignore the full costs of suppression. Thus, some level of costs greater than the true costs are deemed acceptable in the suppression stage of the sequential model and the remaining costs are shifted to the agency's fire manager.

An important policy implication arises from this result. Specifically, the availability of supplementary suppression funding has the potential to impact an incident commander's heuristic weighting scheme and consequently increase the propensity to accept a sub-optimal solution to the suppression demand problem. Supplementary financing available from the Disaster Relief Fund can be released to fire management agencies by Congress when suppression expenditures exceed annual budget allotments. Under the WDFA, agencies still retain the authority to borrow funds from non-fire accounts or other pre-suppression budgets to finance emergency suppression efforts, although the need for this practice may be reduced by the availability of additional suppression appropriations (a portion of which are financed through the Disaster Relief Fund).

The resulting optimization problem in the pre-suppression stage represents the first characterization of an equilibrium solution to the "restricted" fire management problem that preserves an assumption of complementarity between pre-suppression and suppression. Donovan and Rideout (2003) correctly note that Sparhawk's original assumption of negative dependency between program components in the restricted fire management problem will necessarily generate either no solution or a different minimum solution than in the case where components are simultaneously chosen within a unified budgeting structure. However, as we have shown here, the assumed dependency between S and P (imposed by a fragmented budgeting process) can produce an identical solution to the social planner's problem with simultaneously determined inputs. This result will hold so long as: 1) the relationship between P and S is complementary, and 2) the ICT aspires to achieve the global minimum of costs and damages rather than some satisfactory level.

Whether suppression and pre-suppression inputs are complements or substitutes remains an active area of research. For example, in a recent study Gonzalez-Caban et al. (2017) were not able to distinguish a general relationship between the suppression costs and the acres of fuels treated within the burned area prior to the fire. Hence, in some regions, these two inputs could be viewed as complements, whereas in others, as substitutes. Using our model to interpret these empirical results, the appearance of substitutability could be explained by variation in θ (by Proposition 1), whereas the complementarity between the inputs could be explained by a fixed θ. Controlling for the influence of θ and testing the hypothesis presented in Proposition 1 remains a potential opportunity for future empirical work.

Using the sequential model proposed in the present paper, our research focuses on the influence of satisficing behavior on the socially efficient fire management outcome in a deterministic setting. The sequential model provides some explanation for the observed increase of agency budget shares devoted to wildfire suppression, although more work is needed to parse out the relative influence of this externality from other characteristics of incident commanders, including their risk tolerance, aversion to downside risk exposure, or aversion to ambiguous risks (Maguire and Albright 2005; Wilson et al. 2011; Wibbenmeyer et al. 2013; Hand et al., 2017). These additional considerations may be necessary for understanding the optimal design of contracts to better align the shared objectives of incident commanders and agency administrators.

An extension of the model to a more dynamic setting could also be warranted if the pre-suppression expenditures are treated as an investment to build "capital" that acts to lower the expected fire damages for multiple subsequent periods. The static model presented in this paper can be thought of as the steady state representation where an agency administrator (leader) has furthermore learned the type of the incident commander (follower). As a related matter, another interesting extension would be to investigate the effects of different forms of uncertainties on the program expenditures. For example, if the agency administrator in the pre-suppression stage does not know *a priori* the type of the incident commander that will oversee suppression (e.g. high-cost or low-cost), but the incident commander does know their own type, the implications of such asymmetric information becomes an interesting consideration in an optimal contract design problem. These uncertainties may further distort the sequential allocation from the Pareto efficient outcome if contracts have not been designed to control for their associated constraints on a socially efficient solution.

1.6. Conclusion

To model the effect of a fragmented budgeting sequence, we extended the C+NVC model to a game-theoretic framework. The sequential model enables alternative assumptions about the fraction of allocated suppression funding honored by a contracted ICT to effect the equilibrium outcome at the time their demand for suppression is expressed. The resulting allocation of funding to each component of the federal fire program is characterized by a "Stackelberg" solution to the leader-follower game structure. We have shown that such a solution is identical to the one derived under the standard C+NVC model when the ICT places equal weight on both the NVC component and the suppression component of their dual objective function. When ICTs fail to internalize the full costs of suppression into their suppression strategy, the allocation of funding to each component will of the fire program can be expected to deviate from the socially efficient allocation derived under the standard (unified) C+NVC budgeting model.

With the capacity to utilize supplemental funding and reimburse borrowed accounts, there may still be a tendency for incident managers to externalize a portion of total suppression costs. However, the burden of additional suppression costs is not left with the fire management agency itself, but instead with other emergency management agencies. While annual federal fire management appropriations may regain some stability from year-to-year as fire borrowing practices are expected to phase out under the new funding rule, the ccapacity to shift the cost of suppression onto other federal agencies is not likely to provide adequate incentives for incident managers to consider the full costs of suppression. The continuation of a fragmented budgeting structure along with the capacity to utilize the supplementary portion of the Disaster Relief Fund should not be expected to shift fire management expenditure shares away from suppression if the conditions derived in this chapter hold true.

Appendix A: Proof of Proposition 1

Taking the partial derivative of the ICT's best response function(eq. 10) with respect to θ gives:

$$\frac{\partial S(P, W_S, \theta)}{\partial \theta} = \frac{S(P, W_S, \theta)}{\gamma_2 - 1}\left(\theta^{-1} - \gamma_1 P^{-1}\frac{\partial P}{\partial \theta}\right).$$

To determine the sign of the above partial derivative, we need to find an expression for $\frac{\partial P}{\partial \theta}$. Let the first derivative of the first stage objective function (c.f. eq. 11) be denoted by G. Using the implicit function theorem, we can write the partial derivative of interest as follows:

$$\frac{\partial P(W_P, W_S, \theta)}{\partial \theta} = -\frac{\frac{\partial G}{\partial \theta}}{\frac{\partial G}{\partial P}}.$$

The denominator is positive by the assumption that the second-order condition holds (see Appendix B). It can be shown that:

$$\frac{\partial G}{\partial \theta} = -\frac{\gamma_1(W_S S - \gamma_2 \beta P^{\gamma_1} S^{\gamma_2})}{(\gamma_2 - 1)^2 P\theta}.$$

Using the above expression and $\frac{\partial G}{\partial P}$ from Appendix B, we can now rewrite $\frac{\partial P}{\partial \theta}$ as:

$$\frac{\partial P(W_P, W_S, \theta)}{\partial \theta} = \frac{P}{\theta}\left(\frac{W_S S - \gamma_2 \beta P^{\gamma_1} S^{\gamma_2}}{(\gamma_1 + \gamma_2 - 1)(W_S S - \beta P^{\gamma_1} S^{\gamma_2})}\right).$$

The denominator is positive (see Appendix B). Thus, for $\frac{\partial P}{\partial \theta} > 0$ to hold, it must be the case that $W_S S - \gamma_2 \beta P^{\gamma_1} S^{\gamma_2} > 0$. This condition can be written as:

$$\gamma_2 < \frac{W_S S}{\beta P^{\gamma_1} S^{\gamma_2}}.$$

Recall that the FOC in the suppression stage is:

$$\theta W_S S - \gamma_2 \beta P^{\gamma_1} S^{\gamma_2 - 1} = 0$$

Which is equivalent to:

$$\frac{\gamma_2}{\theta} = \frac{W_S S}{\beta P^{\gamma_1} S^{\gamma_2}},$$

which proves that $\frac{\partial P}{\partial \theta} > 0$.

We can now rewrite $\frac{\partial S}{\partial \theta}$ as:

$$\frac{\partial S(P, W_S, \theta)}{\partial \theta} = \frac{S}{\theta}\left(\frac{W_S S - (1-\gamma_1)\beta P^{\gamma_1} S^{\gamma_2}}{(\gamma_1 + \gamma_2 - 1)(W_S S - \beta P^{\gamma_1} S^{\gamma_2})}\right).$$

The denominator is again positive. Hence the numerator determines the sign. This proves Proposition 1: when $\frac{W_S S}{\beta P^{\gamma_1} S^{\gamma_2}} < 1 - \gamma_1$,

$$\frac{\partial S^*}{\partial \theta} < 0, \frac{\partial P^*}{\partial \theta} > 0$$

And when $\frac{W_S S}{\beta P^{\gamma_1} S^{\gamma_2}} > 1 - \gamma_1$,

$$\frac{\partial S^*}{\partial \theta} > 0, \frac{\partial P^*}{\partial \theta} > 0.$$

Finally, note that the SOSC imposes the following restriction which supports the possibility to have $\frac{W_S S}{\beta P^{\gamma_1} S^{\gamma_2}} < 1 - \gamma_1$,

$$0 < \frac{W_S S}{\beta P^{\gamma_1} S^{\gamma_2}} < 1.$$

Appendix B: Second order sufficiency condition

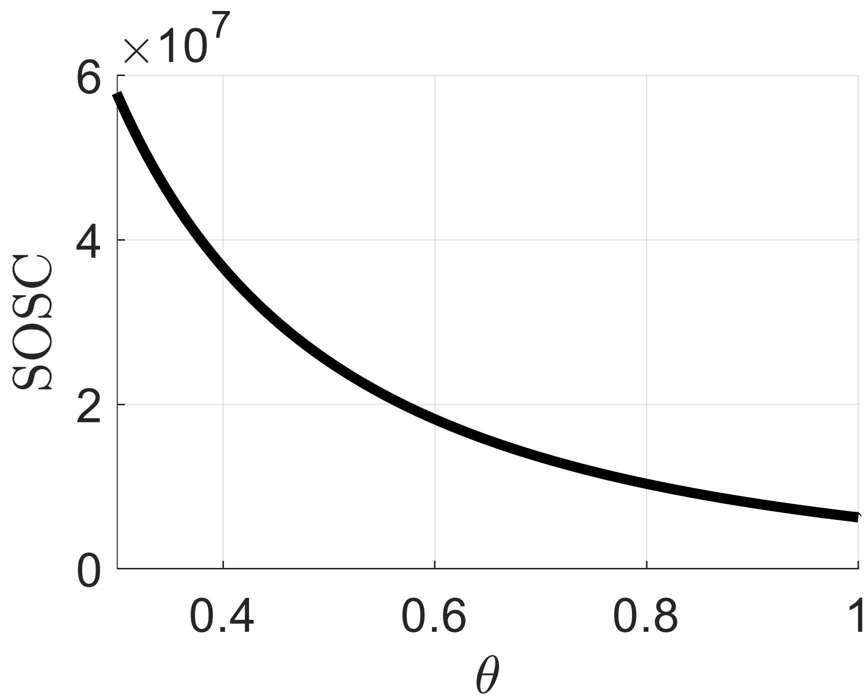
To investigate the feasibility of Proposition 1, we must ensure that the second order sufficiency condition (SOSC) is satisfied. Applying condition (9) gives:

$$\frac{\partial G}{\partial P} = \frac{\gamma_1(\gamma_1 + \gamma_2 - 1)(W_S S - \beta P^{\gamma_1} S^{\gamma_2})}{(\gamma_2 - 1)^2 P^2} > 0.$$

For the above condition to hold, we must have $\gamma_1 + \gamma_2 - 1 < 0$ and $W_S S - \beta P^{\gamma_1} S^{\gamma_2} < 0$.

Equation (12) is plotted against θ in Figure 1.9. The figure shows that the sufficiency conditions can be satisfied under certain values of θ and the parameters of the NVC function $(\gamma_1, \gamma_2, \beta)$. Under certain functional forms of the objective function (including Cobb-Douglas as shown here), the second-order condition of the agency administrator's restricted problem is a minimum. However, a solution will not necessarily hold in general.

Figure 1.9 - Second-order condition of the restricted C+NVC problem



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CHAPTER 2: THE INFLUENCE OF RISK ATTITUDES ON SUPPRESSION SPENDING AND ON WILDLAND FIRE PROGRAM BUDGETING

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2.1. Introduction

In seven of the last ten fiscal years, agency-wide suppression expenditures in the U.S. Forest Service have exceeded 50% of total fire management expenditures (Hoover and Lindsay, 2017). This expenditure trend is generally viewed as counterproductive to other land management objectives, including fire risk mitigation, as it consumes larger proportions of the agency's appropriated budgets (USFS 2015; Hoover and Lindsay, 2017). Similar, albeit less drastic, trends are also observable in other land management agencies (Stephens et al. 2016), while the overall trend is expected continue unabated into the near future (USFS, 2015). To address this problem, land management agencies have continued their development of risk analysis tools to better inform budgeting and resource allocation decisions across land management organizations with a common objective (Thompson and Calkin, 2011; Taber et al., 2013; GAO, 2015; Thompson et al., 2017).

A risk management framework represents a strong departure from early 20th century suppression policies which relied heavily on heuristic "rules of thumb" (Blattenberger et al., 1984). For example, the 10 A.M. policy of 1935 required the full suppression of a wildfire before 10 A.M. the day after its discovery without full consideration of costs, risk, or potential benefits of allowing it to burn. In stark contrast, a key objective of recent legislation (such as the 2001 update to the Federal Fire Management Policy and the 2009 FLAME Act) is to utilize risk analysis for requesting and allocating scarce budgets across different programs and regions within the fire management organization to enable cost-effective suppression response (Jewell and Vilsack, 2014). The aim of these policies is to reinforce a goal of cost efficiency and to require the use of regional and national scale budgeting and fire risk management (Hann and Bunnell, 2001; Fire Executive Council, 2009).

However, there is potential for risk attitudes to override the success of such analyses (Katuwal et al., 2017; Hand et al., 2015; Thompson, 2014; Calkin et al., 2011), and to perpetuate the tendency for larger percentages of public land management expenditures to be allocated towards suppression efforts instead of risk reduction activities. Formally defined, risk attitudes are a decision-maker’s preference for higher-order characteristics of their payoff distribution, which contain more information than just the expected value of net benefits. Using panel data on large wildfires managed during the period 2007-2011, Hand et al. (2017) find that differences across incident management teams can account for up to 14 percent of observed variation in the demand for suppression resources. The authors attribute these differences to alternative levels of risk aversion across incident management teams. Hence, risk preferences on the ground may continue to have a significant impact on the allocation of resources in the overall fire management program.

The Cost Plus Net Value Change (C+NVC) model forms the standard approach for determining the cost-efficient allocation of budgetary resources in a fire management program (Rossi and Kuusela, 2019; Rideout et al., 2008; Donovan and Rideout 2003). It extends the original Cost Plus Loss model proposed by Sparhawk (1925) by including broader measures of benefits and costs from wildfires that go beyond financial damages. Rossi and Kuusela (2019) use the C+NVC model to examine how mis-aligned objective functions of incident managers and wildfire program administrators can lead to inefficient program outcomes. However, the specific role of varying risk attitudes on program efficiency and their effects on budget allocation have not been formally examined, despite the wide recognition of their importance. One exception is Donovan and Brown (2005) who use the expected utility model to propose an alternative incentive structure that achieves more efficient program outcomes. However, they do not assess the impacts of varying risk attitudes on budget allocations or the expected net social benefit of the program.

The purpose of this chapter is to use an expected utility model together with the C+NVC framework to examine the effects of organizational risk attitudes on program efficiency and budget allocations. Our model characterizes the organization's demand behavior when contracted incident managers display different attitudes towards risk and uncertainty. In this paper, we consider two such attitudes. Specifically, we consider an incident manager's aversion to a higher variance of possible payoffs (risk aversion) or their tolerance for greater exposure to "catastrophic" losses (downside risk aversion). The latter is intrinsically related to skewed payoff distributions which are, as we will argue, a pervasive feature of wildland fire incidents. We show that the possibility of catastrophic losses can drive an even bigger wedge between the efficient budget allocation and the one where risk attitudes contribute to decision making.

In the U.S., federal funding for both suppression and pre-suppression operations are initially allocated through annual appropriations, although additional funding for suppression is available through emergency accounts or the Federal Emergency Management Agency. Given the inherent uncertainties on the severity of fire seasons, the actual spending levels on different wildfire program components are not determined simultaneously, but rather sequentially as funding from these additional sources are requested throughout a fiscal year. Agencies may request the use of these resources when suppression appropriations are at risk of exhaustion and can be accessed with approval of Congress. The availability of emergency financing for suppression effort has been identified as one of the key drivers of increasing suppression costs and the consequent inefficiencies in federal management effort (Donovan and Brown, 2005; Rossi and Kuusela, 2019). The inefficiencies arise when spending on suppression is determined reactively during the fire season as a shortrun factor demand problem. It has been shown that the sequential structure of the problem does not generate this inefficiency alone, but it can impact the resulting expenditure allocation when suppression costs are not internalized by the incident manager, but are externalized onto another portion of the agency's budget, another federal agency, or onto the general public through off-budget financing (Rossi and Kuusela, 2019).

Such a spending structure, where actual expenditures on different program components are determined reactively based on the severity of the fire season, is more accurately characterized by a two-stage decision problem. In our model, budget allocations are determined by a leader-follower (Stackelberg) game, where the leader is the wildland fire program administrator who decides pre-suppression expenditures and the follower is the incident commander whose services are contracted by the fire program administrator to determine suppression demand. The incident commander may exhibit different degrees of risk aversion when deciding the level of suppression spending, whereas the program administrator is assumed to be risk neutral. The leader in the game chooses and commits to a certain level of pre-suppression spending given the known response function of the risk averse incident commander. The two decisions jointly determine the net value change (NVC); hence the leader can strategically influence the follower's decision with a given input use. The role and purpose of the fragmented (sequential) spending decisions in our model is twofold: 1) it describes the chronological structure of the full budgeting decision within management agencies, and 2) it enables us characterize the qualitative effect of risk averse incident managers on the overall spending and on the allocation of spending.

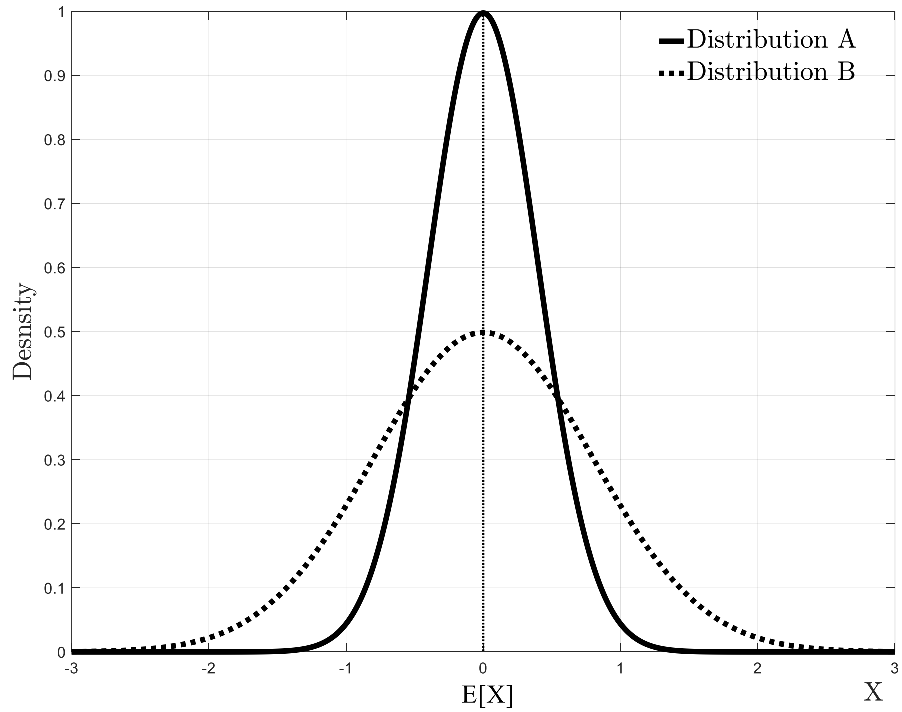
We derive analytical results using a constant absolute risk aversion (CARA) functional form which shows how risk aversion can lead to increased suppression spending and reduced pre-suppression activities compared to the risk neutral benchmark case. Using a numerical simulation model, we also examine the program efficiency outcomes under decreasing absolute risk aversion (DARA). We parameterize the model to reflect a representative allocation that is typical of annual management decisions made at the landscape or regional level. The model assesses the potential for various components of an incident manager's risk premium to alter their choice of suppression demand relative to an incident manager who displays a neutral attitude towards risk. These factors are shown to have an influence on the organization's optimal allocation of budgets and the share of overall expenditures devoted to suppression. We also compare the numerical results derived from the sequential model to a unified model where a risk averse planner can decide both suppression and presuppression expenditures. The impact of risk aversion on program outcomes is magnified in the sequential case.

The rest of the chapter is organized as follows. Section 2 reviews the literature on risk attitudes in wildfire incident management. Section 3 presents a two-stage game to capture these risk attitudes as additional determinants of demand within a fire management framework. In Section 4, we present the comparative statics of a numerical model using a specified functional form for the organization's fire management technology. In the last section, we discuss policy implications of the model's results and directions for further research.

2.2. Risk attitudes in public incident management

Risk attitudes refer to a decision maker's preferences over characteristics of a payoff distribution when faced with a risky situation. Consider first that a *risk neutral* decision-maker faced with multiple uncertain alternatives will simply select the alternative with the highest expected payoff. In contrast, a *risk averse* decision maker will be satisfied with a lower payoff, on average, to obtain a lower variance of potential outcomes. To further illustrate the concept of "second-order stochastic dominance," Figure 2.1 depicts two payoff distributions, A and B, with the same expected value. For a risk averse decision-maker, distribution A will be strictly preferred to distribution B, whereas a risk neutral decision maker would be indifferent between the two payoff distributions.

Figure 2.1 - Illustration of Second-order stochastic dominance



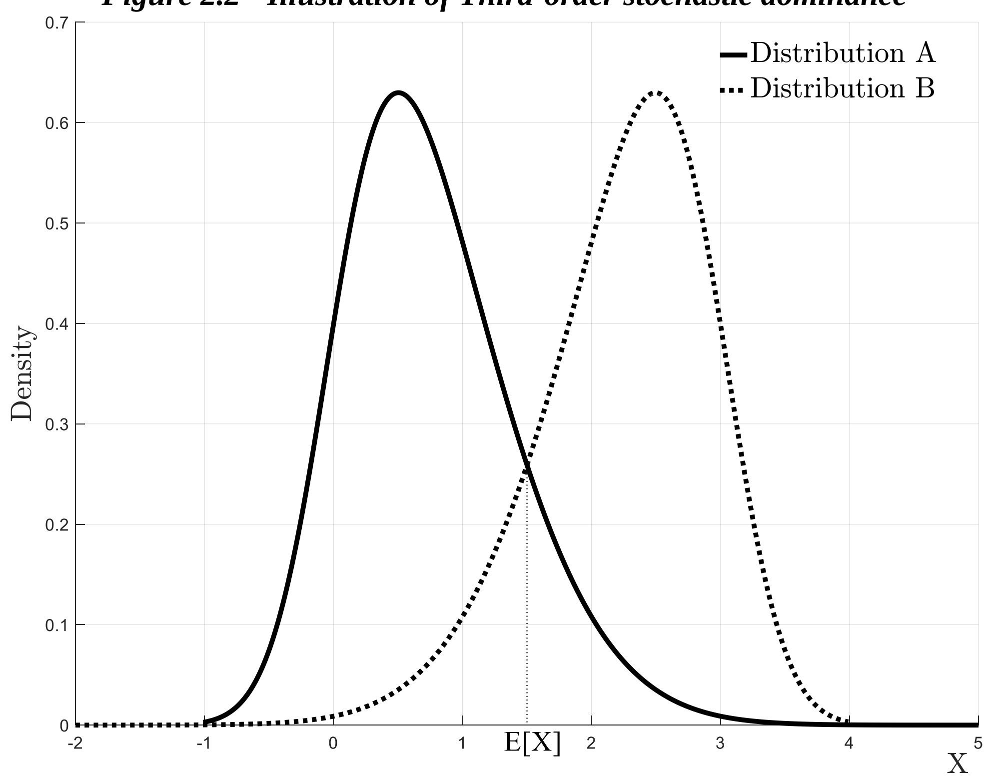
Risk aversion has been suggested as a cause of excessive suppression response within fire management organizations (Maguire and Albright, 2005; Blattenberger et al., 1984) and the tendency can vary locally across incidents or incident managers (Hand et al., 2017). Early attempts to assess the presence of risk aversion amongst wildfire managers found no evidence of risk aversion in the context of a multi-attribute utility model (Teeter and Dyer, 1986). However, more recent work has found stronger evidence of risk aversion. A survey of incident managers, who are contracted by land management agencies to administer tactical responses during large fire suppression efforts, indicated risk averse behavior (Canton-Thompson, 2006).

The most recent empirical evidence of risk averse incident managers supports the expected utility model presented by Hand et al. (2017). The authors derive an expression for the optimal suppression demand for a representative risk averse incident manager facing uncertain returns from the deployment of suppression resources. The derived demand for suppression effort is shown to vary with the parameters of an expected utility function, which implies that the incident manager's risk type can influence the agency's demand for fire suppression resources. In other words, greater risk aversion of a contracted incident management team can lead to larger or more frequent requests for additional resources, thereby influencing federal suppression expenditures. Empirical evidence of suppression demand behavior amongst incident managers supports this theory (Hand et al., 2017). However, more work is needed to determine if these group-level differences are determined by other unobservable characteristics of incident management teams besides varying levels of risk aversion.

For example, ignoring the higher-order approximations of a decision-maker's expected utility can mask the possibility for a decision-maker to display positive skewness preference (Scott and Horvath, 1980). These preferences may also drive choice behavior as it relates to an incident manager's rational demand response when facing a return distribution with large downside risk potential. Positive skewness preference represents an alternative risk attitude than what has been previously considered in the wildfire management literature. A decision-maker that is *averse to downside risk* will accept some lower payoff, on average, to maintain a payoff distribution with lower exposure to left-tailed risks. Given a choice between two risky alternatives with the same average payoff and the same variance of payoffs (such as those depicted in Figure 2.2), a decision-maker with a low tolerance for downside risk will strictly prefer the alternative with a larger skewness (distribution A) to the alternative with a lower skewness (distribution B). This reflects “third-order stochastic dominance” of alternatives preferred by a downside-risk averse decision maker (Menezes et al., 1980).

Empirical evidence of aversion to downside risks has been shown to be a characteristic of decision makers in many different settings, specifically those in the agricultural sector (see Antle, 1987) and those in the financial sector (see Miller and Leiblein, 1996). However, the potential for downside risk aversion to affect the allocation of public budgets for natural disaster protection (or specifically wildfire protection) has not been formally addressed in the literature. This paper shows that knowledge of higher order approximations of the decision-maker’s expected payoff function may help to explain the choice of suppression strategy in low- vs. high risk areas as a result of stronger preference for third moment characteristics of the benefit distribution.

Figure 2.2 - Illustration of Third-order stochastic dominance



2.2.1. Incorporating manager risk attitudes in the sequential model

The standard theory of wildfire economics characterizes a social planner's efficient fire management outcome as the optimal demand for fire management effort (given exogenous prices) which minimizes the sum of total program costs plus net economic damages from fire effects or "C+NVC" (Mills and Bratten, 1982; Donovan and Rideout, 2003). Duality results apply to this framework such that the model is equivalently stated as a maximization of net fire effects benefits less the costs of investments in fire management (Rideout and Omi, 1990). Computational extensions of the model are used to solve for a landscape's optimal demand for fire management effort and are used to support land management agencies that seek to request an efficient level of annual funding to fulfill fire policy obligations (e.g. Rideout et al., 2014; Calkin et al., 2010).

The above empirical evidence of suppression demand behavior suggests that it is possible for incident managers to display a host of rational responses to risk when facing a decision with uncertain outcomes and that risk attitudes may vary across incident managers (Hand et al., 2016; Blattenberger et al., 1984). Few studies have examined the effect of this risk aversion on the share of annual agency expenditures allocated towards suppression effort. This motivates a modification of the sequential wildfire economics model to investigate the influence of an incident manager's risk attitudes on the fire program's overall efficiency and budget allocation.

2.3. Model

The organization's optimal demand for fire management effort is found using a sequential decision framework, in contrast to the socially efficient solution of the standard model. The existence of an equilibrium in this decision framework rests on an assumption of sequential rationality where the agency administrator (i.e. the leader) maintains complete information about the demand response of a risk averse incident manager (i.e. the follower) during future wildfire events. Similar to Donovan and Brown (2005), the assumption of a risk-neutral incident manager is relaxed to explore the potential for the risk attitudes of incident managers to affect the equilibrium allocation. We further extend on the expected utility framework by coupling it with the sequential C+NVC framework presented by Rossi and Kuusela (2019) and by including third-order effects of risk. The equilibrium concept for a game with this structure is a subgame-perfect Nash equilibrium (SPNE) and is solved using backward induction (Varian, 1992). In the backward induction procedure, the solution to the follower's problem represents the outcome for the second stage solution and is then used to find the leader's optimal strategy in the first stage. Table 2.1 provides a list of variables and parameters used in the numerical representation of the two-stage game.

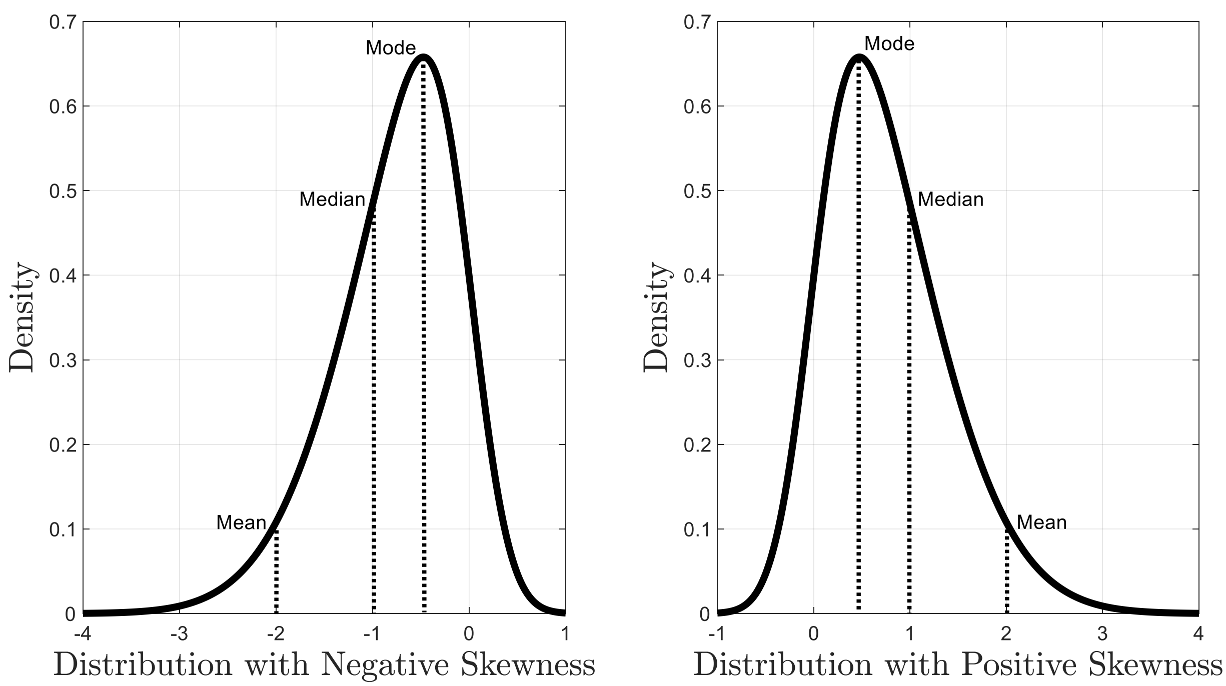
Table 2.1 - Variables and parameters used in sequential wildfire economics model

	Endogenous Parameters	**Domain**
μ	Mean of net value change from fire effects	$(-\infty, \infty)$
ν	Variance of net value change from fire effects	$[0, \infty)$
φ	Skewness of net value change from fire effects	$(-\infty, \infty)$
	Decision Variables	**Domain**
P	Pre-suppression effort (leader's strategy)	[0,∞)
S	Suppression Effort (follower's strategy)	[0,∞)
	Exogenous Parameters	**Domain**
W_P	Unit cost of presuppression effort (in millions of $)	0.25
W_S	Unit cost of suppression effort (in millions of $)	0.45
α	Parameter of the net value change function (in millions of $)	4.50
β	Factor productivity of management effort (in millions of $)	2.15
(γ_1, γ_2)	Output elasticities of P and S	(0.085,0.055)
r	Incident manager's level of risk aversion	$r \in [0,1]$
k	Incident manager's level of downside risk aversion	r^2
$\boldsymbol{\omega}$	A vector of parameters describing shape of the random variable θ	$\boldsymbol{\omega} \in \mathbb{R}^{\boldsymbol{n}}$
σ_θ	Special case of $\boldsymbol{\omega}$ (st. dev. of θ)	2.65
	Random Variables	**Distribution**
θ	Multiplicative risk parameter	$\theta \sim N(1, \sigma_\theta)$ or $\theta \sim lognormal\left(\ln \frac{1}{\sqrt{\sigma_\theta + 1}}, \sqrt{\ln\left(\frac{\sigma_\theta^2}{1} + 1\right)}\right)$
V	Net value change from fire effects	$V \sim N(\beta P^{\gamma_1} S^{\gamma_2} - \alpha\ , \sigma_\theta)$ or $V \sim lognormal(a, b)$

2.3.1. Suppression and Presuppression inputs

We start with an assumption of a risk averse incident manager. Incident managers must determine the level of suppression effort to employ but face uncertain levels of net value change depending on the type and amount of assets at risk of wildfire damage. Wildfires that burn in close proximity to the wildland-urban interface, near timber plantations, or over sensitive wildlife habitat, may expose the public to a larger probability of highly damaging outcomes. When fires burn in these areas, the net value change distribution is likely to display a greater exposure to downside risk as shown in Figure 2.3 (left). If instead, wildfires burn over forest ecosystems that benefit from wildfire exposure (such as stands of fire dependent tree species) or over wildlands farther from human developments, the net value change distribution is less likely to expose the public to highly damaging outcomes. In these cases, the net value change distribution is more likely to display greater upside risk as in Figure 2.3 (right).

Figure 2.3 - Negative and Positive Skewness



In the event of an unplanned wildfire, the incident manager is contracted by the district's administrator to oversee the deployment and movement of suppression resources (S) across administered lands. Let the term $V = V(P, S, \theta)$ represent the net value change (NVC) on unplanned fire effects (i.e. the ecologically beneficial or restorative effects of wildfire less any damages to human or environmental assets) where P is the level of pre-suppression effort and θ is a random variable with a known probability density function $f(\cdot)$. The NVC function is increasing in the application of both inputs $\left(\frac{\partial V}{\partial S} > 0, \frac{\partial V}{\partial P} > 0\right)$ but at a decreasing rate $\left(\frac{\partial^2 V}{\partial S^2} < 0, \frac{\partial^2 V}{\partial P^2} < 0\right)$. We assume that the cross-partial derivative is positive $\left(\frac{\partial^2 V}{\partial P \partial S} > 0\right)$, meaning that the marginal productivity of one input is increasing in the application of the other input. Suppression and pre-suppression have many complementary interactions through their joint technological capacity to reduce wildfire damages and improve the relative productivity of one another (Hirsch et al., 1998; Mogghaddas and Craggs, 2007; Haight and Fried, 2007). For example, fuel reduction in the wildland-urban interface (WUI) may create safer environment for firefighters to operate and hence render firefighting efforts more productive.[8]

For now, we impose limited structure on each incident manager's Bernoulli utility function u. Specifically, we only assume that it is increasing and concave in V. Each incident manager's expected utility function is defined as:

$$\mathrm{E}[u] = \int_{-\infty}^{\infty} u(V) f(V) dV.$$

---

[8] The result from Mogghadas and Craggs (2007) suggests that increases in pre-suppression investment (specifically a fuel treatment) increased the marginal productivity of subsequent suppression effort through increased penetration of fire retardant, a reported improvement in visual contact between incident manager and fire crews, safer access to fires during suppression response, and quicker suppression of spot fires.

The incident manager's expected utility function is approximated as a certainty equivalent, CE, given by an additive combination of expected net value change, $\mu \coloneqq \mathrm{E}[V]$, minus a risk premium: $CE = \mu - R$. The risk premium (R) is referred to as the "cost of risk" and is comprised of higher order moments of the return distribution weighted by coefficients describing the decision-maker's aversion to such characteristics of the return distribution. Using a well-known approximation result (e.g. Chavas, 2004), the risk premium can be written as a function of variance (ν) and skewness (φ) of the random return distribution. Note that the skewness parameter φ can take positive or negative values depending on the direction of the skew.

More specifically, the third order Taylor approximation of the expected utility function around the mean is:

$$\mathrm{E}[u] \approx u(\mu) + \frac{u''(\mu)}{2!}\nu + \frac{u'''(\mu)}{3!}\varphi.$$

Moreover, the risk premium can be defined as using the following equation:

$$\mathrm{E}[u] = u(\mu - R).$$

The above condition means that the incident commander is indifferent between the expected utility and the sure payoff, where the latter is defined as the utility from the expected NVC net of the risk premium. Taking the second order Taylor approximation of the right-hand side around the mean ($R = 0$) gives:

$$\mathrm{E}[u] \approx u(\mu) - u'(\mu)R.$$

Combining the above results yields a local approximation of the risk premium around μ:

$$R \approx \frac{1}{2}\frac{u''(\mu)}{u'(\mu)}\nu - \frac{1}{6}\frac{u'''(\mu)}{u'(\mu)}\varphi.$$

where $r = -\frac{u''(\mu)}{u'(\mu)} > 0$ and $k = \frac{u'''(\mu)}{u'(\mu)} > 0$.

The term r measures the Arrow-Pratt coefficient of absolute risk aversion and will be positive under either an assumption of *constant* absolute risk aversion (CARA) or *decreasing* absolute risk aversion (DARA). Notice that the risk premium is increasing with a larger variance of net value change but is decreasing as the return distribution displays larger positive skewness. The latter is explained by the fact that larger positive skewness decreases exposure to downside risk by limiting the likelihood of observing fires with damages well below the most likely level. The coefficient of precaution, k, captures an incident manager's tolerance for managing fires with higher potential for "catastrophic" losses (that is, fires with damaging outcomes several standard deviations below the mean outcome). It can be shown that DARA preferences exhibit downside risk aversion (Liu and Meyer, 2012). This implies that the coefficient k is positive under an assumption of DARA and that distributions with a larger right-tail skewness are more desirable than distributions with smaller right-tails or distributions with negative (left-tailed) skewness. This is shown to influence demand behavior in an extension of the numerical example presented in Section 5. The same result also holds with an alternative assumption of CARA as we will show next.

In what follows, we maintain an assumption of CARA preferences to derive analytical results. Under the assumption that fire management effort influences the mean, variance, and skewness of net value change from fire effects, we can characterize the incident manager's choice of suppression effort in the second stage of the sequential game. Thus, we denote the mean as: $\mu = \mathrm{E}[V(P,S,\theta)]$, the variance as: $\nu = \mathrm{var}\big(V(P,S,\theta)\big)$, and the skewness as: $\varphi = \mathrm{skew}\big(V(P,S,\theta)\big)$. In this stage, the incident manager solves for a level of suppression demand such that they maximize their certainty equivalent minus investment costs given a constant unit cost of suppression effort (W_S).

$$\max_{S\geq 0}\left\{\mu - \frac{r}{2}\nu + \frac{k}{6}\varphi - W_S S\right\}.$$

(1)

Under the assumption of a CARA utility function, we have $k = r^2$.[9] This implies that downside risk aversion is a quadratic function of the incident manager's level of risk aversion. We focus on interior solutions ($S > 0$) given by the root of the first-order necessary condition from (1):

$$\frac{\partial \mu}{\partial S} - \frac{r}{2}\left(\frac{\partial \nu}{\partial S}\right) + \frac{r^2}{6}\left(\frac{\partial \varphi}{\partial S}\right) - W_S = 0.$$

(2)

A maximum of (1) also requires the following sufficiency condition to be satisfied:

$$\frac{\partial^2 \mu}{\partial S^2} - \frac{r}{2}\left(\frac{\partial^2 \nu}{\partial S^2}\right) + \frac{r^2}{6}\left(\frac{\partial^2 \varphi}{\partial S^2}\right) < 0.$$

(3)

Where condition (3) holds, the incident manager's best response function, $S(P, W_S, r, \boldsymbol{\omega})$, is defined implicitly by equation (2) and gives the incident manager's choice of suppression demand for any prior choice of P, the unit costs of suppression, and their level of risk aversion (r). The term $\boldsymbol{\omega}$ reflects any collection of parameters in the distribution function $f(\cdot)$ that describe its shape. When $r = 0$ (indicating a risk neutral incident manager), equation (2) collapses to one of the usual first-order conditions found in the standard C+NVC model.[10] The

---

[9] This can be derived using:

$$\frac{u''(x)}{u'(x)} = r$$

Take the total derivative:

$$\frac{u'''}{u'}dx - \frac{u''(x)}{u'(x)^2}u''(x)dx = dr$$

A small change in x gives:

$$\frac{u'''}{u'} - r^2 = 0$$

[10] This also happens whenever $r = 3\nu/\varphi$ which implies that $R = 0$.

incident manager will thus choose a level of suppression effort such that the expected marginal value is equal to the unit cost of suppression effort. It is shown by Rossi and Kuusela (2019) that such a solution to the sequential model with a rational and risk neutral incident manager will be identical to the solution derived by the standard C+NVC model.

With accurate anticipation of the incident manager's best response, the administrator takes it into account when deciding the level of the pre-suppression effort. The first-stage problem can be written as

$$\max_{P\geq 0} \mathrm{E}[V(P, S(P, W_S, r, \boldsymbol{\omega}), \theta) - W_P P - W_S S(P, W_S, r, \boldsymbol{\omega})]. \tag{4}$$

Notice that an assumption of a risk-neutral administrator is maintained and is a typical assumption for public fire management problems (Rideout et al., 2008). As summarized by Blattenberger (1984), the assumption of risk neutrality reflects the agencies' long term objective and their capacity to manage a diverse set of fire-affected assets that are spread across a wide group of citizens (Arrow and Lind, 1970; Samuelson, 1964). This assumption adheres to the mutuality principle (Hun Seog, 2010), suggesting that the greater number of individuals protected with independent risk, the variance of the portfolio of stakeholders tends towards zero.[11] To achieve the best possible outcome, the agency administrator solves the first-order condition (5) for the optimal level of pre-suppression demand, $P^*(W_P, W_S, r, \boldsymbol{\omega})$:

$$\frac{\partial V(\cdot)}{\partial P} + \frac{\partial V(\cdot)}{\partial S}\left(\frac{\partial S(P, W_S, r, \boldsymbol{\omega})}{\partial P}\right) - W_P - W_S\left(\frac{\partial S(P, W_S, r, \boldsymbol{\omega})}{\partial P}\right) = 0.$$

[11] It would be possible to model a risk averse administrator. However, there is no evidence that such behavior exists. By assuming risk averse incident commanders and a risk neutral administrator, we are able to derive efficiency implications stemming from empirically reported risk attitudes.

(5)

Embedding this solution in the incident manager's best response function yields the suppression demand function, $S^*(W_P, W_S, r, \boldsymbol{\omega})$. The pair of demand functions represent a SPNE to the two-stage game.

The following proposition collects the main analytical findings from the above model:

Proposition 1:

a) *Assume that the net value change from fire management effort is asymmetrically distributed so that the sample skewness is nonzero. When suppression effort decreases the variance* $\left(\frac{\partial v}{\partial S} < 0\right)$ *and increases the skewness* $\left(\frac{\partial \varphi}{\partial S} > 0\right)$*, we have*:

$$\frac{\partial S}{\partial r} > 0.$$

However, when suppression effort decreases the skewness $\left(\frac{\partial \varphi}{\partial S} < 0\right)$ *the sign of* $\frac{\partial S}{\partial r}$ *will depend primarily on the relative magnitude of the partials* $\frac{\partial v}{\partial S}$ *and* $\frac{\partial \varphi}{\partial S}$.

b) *Given* $\frac{\partial^2 V}{\partial P \partial S} > 0$*, suppression is increasing in pre-suppression (implying strategic complementarity) when the following conditions hold:* $\frac{\partial^2 v}{\partial S \partial P} < 0$ *and* $\frac{\partial^2 \varphi}{\partial S \partial P} > 0$.

c) *The effect of higher risk aversion on pre-suppression is ambiguous:*

$$\frac{\partial P}{\partial r} \gtreqless 0.$$

Proof: See Appendix A.

Intuitively, the first assumption of Proposition 1 $\left(\frac{\partial \varphi}{\partial S} > 0\right)$ suggests that when forest fires occur in areas with high-valued assets at risk (such as in the WUI) there is potential for suppression effort to increase the skewness of the return distribution (by limiting large downside risk and hence making the skewness less negative). In such cases, net value change is likely negative so we allow the value of the partial effect $\left(\frac{\partial \varphi}{\partial S}\right)$ to be positive. In these cases, greater risk aversion raises the demand for suppression $\left(\frac{\partial S}{\partial r} > 0\right)$ and this effect is enhanced by the presence of a skewed NVC distribution in comparison to a symmetric NVC distribution.

Alternatively, if forest fires burn over areas that benefit from fire (such as certain forest cover types in fire-dependent ecosystems) the net value change from fire effects is positive. Thus, there is less potential for full suppression effort to decrease the potential for large downside risk. In these cases, less aggressive suppression strategies like "point-protection" or "wildfire monitoring" are likely to be more efficient choices as they reduce the variance of potential outcomes. Suppression response will thus have less impact on the skewness of the return distribution and may even decrease the skewness of net value change by limiting upside risk potential (so we can alternatively allow for $\left(\frac{\partial \varphi}{\partial S}\right) < 0$). In this case, we can expect the magnitude of the partial effect $\left(\frac{\partial \nu}{\partial S}\right)$ to actually exceed that of $\left(\frac{\partial \varphi}{\partial S}\right)$, yielding a negative relationship: $\frac{\partial S}{\partial r} < 0$. In these cases where fire effects are beneficial and skewness decreases with suppression effort, greater levels of risk aversion can actually decrease the level of suppression effort employed.

Part b) in Proposition 1 describes how incident commander's best response function varies in the level of pre-suppression. When pre-suppression increases the marginal productivity of suppression input for lowering the variance of net benefits $\left(\frac{\partial^2 \nu}{\partial S \partial P} < 0\right)$ and when pre-suppression increases the marginal productivity of suppression input for raising the skewness (i.e. less negative skew) of net benefits $\left(\frac{\partial^2\varphi}{\partial S\partial P} > 0\right)$, then suppression is increasing in pre-suppression. When this hold, it can be said that the suppression and pre-suppression inputs are strategic complements.

According to part c) in Proposition 1, the effect of increasing risk aversion on pre-suppression is ambiguous. Given the presence of strategic interaction, it is possible that higher risk aversion leads to higher suppression but lower pre-suppression. In effect, with complete information about the incident manager's best response, the administrator can still indirectly influence the overall costs of the program by strategically cutting back on the demand for pre-suppression. This induces the incident commander to use a lower level of suppression effort than in the case where no strategic action is taken by the administrator.

The above results are derived using the assumption of sequential decision making. As a useful benchmark for assessing the significance of the strategic dimension of the expenditure allocation decision, we also investigate the properties of a unified budgeting problem where the program administrator decides both input expenditures and so faces no opportunity for strategic behavior. However, we allow for the planner in the unified model to exhibit risk aversion in order to facilitate comparison to the result derived in Proposition 1. The following proposition summarizes the main result with respect to the effect of risk aversion on expenditures in a unified model.

Proposition 2:

Assume that the payoff is symmetrically distributed around the mean so that $\varphi_S = 0$ *and additionally that* $\nu_P < 0, \nu_S < 0, \nu_{SS} > 0, \nu_{PP} > 0,$ *and* $\nu_{PS} < 0$. *If risk aversion were to enter* *the unified budgeting problem (where P and S are chosen simultaneously), then increasing levels of risk aversion will always raise the demand for both P and S.*

Proof: See Appendix B.

The assumptions with respect to positive second partial derivatives of the variance function reflect diminishing marginal productivity of an input in reducing the variance of the NVC, and the assumption of negative cross partial derivative reflects improved effectiveness of one input in decreasing the variance given a greater application of the other input. The latter assumption was also required for the strategic complementarity to hold in Proposition 1b. In contrast to the sequential model where strategic interaction plays a role, Proposition 2 shows that in the unified model both input uses are likely increasing in risk aversion (given that the assumptions hold). In the sequential model, the response in presuppression can go either way, given the leader's ability to strategically reign in the suppression spending by committing to a lower presuppression investments. We next define a numerical version of the model to further explore the sign of these responses under standard functional form assumptions, and to compare the expenditure allocation form the sequential model and the unified model.

2.3.2. Numerical application

We will use a general Cobb-Douglas technology to parameterize the NVC function. Let θ be a multiplicative risk parameter to introduce the exact form of the random return distribution. This enables the NVC to be expressed as a random variable of the form:

$$V = \theta(\beta P^{\gamma_1} S^{\gamma_2} - \alpha). \qquad (6)$$

In equation (6), α represents the level of net value change attainable if managers were to exert no effort ($P^* = 0, S^* = 0$). If fires burn without any management effort, there will still be some damages to structures and watersheds and also some gains to fire-dependent areas in terms of risk reduction or restoration. When the expected value of θ is one, the expected net value change from fire effects are expressed as:

$$\mu = \beta P^{\gamma_1} S^{\gamma_2} - \alpha. \qquad (7)$$

Now, the variance can be written as:

$$\nu = \left(\sigma_\theta^2 - 1\right)(\beta P^{\gamma_1} S^{\gamma_2} - \alpha)^2, \qquad (8)$$

and skewness as:

$$\varphi = \left(\sigma_\theta^3 - 3\sigma_\theta^2 + 2\right)(\beta P^{\gamma_1} S^{\gamma 2} - \alpha)^3. \qquad (9)$$

See Appendix C for a full derivation of equations (8) and (9). The parameter σ_θ reflects the standard deviation of the multiplicative risk parameter. Larger values of σ_θ reflect a larger variance of net value change.

With the newly derived expressions for the mean (7), variance (8), and skewness of net value change (9), a specific functional form for the incident manager's first-order condition in equation (2) can be obtained and the resulting optimal solution follows from an application of a univariate root-finding algorithm such as bisection (Miranda and Fackler, 2002).

When conditions (2) and (3) are satisfied, the best response function is correctly anticipated by the agency administrator under the assumption of sequential rationality. Hence, the administrator's first stage problem is shown by a specific case of (4), as shown by the objective function in equation (10):

$$\max_{P \geq 0} \; \mathrm{E}[\theta(\beta P^{\gamma_1}[S(P, W_S, r, k, \sigma_\theta)]^{\gamma_2} - \alpha) - W_P P - W_S S(P, W_S, r, k, \sigma_\theta)]. \qquad (10)$$

Numerical solutions to the first stage problem (10) exist when the sufficient condition for a maximum is satisfied. These sufficient conditions are investigated and the solutions to (10) are found in the following section using a sequential-quadratic programming algorithm in MATLAB (Venkataraman, 2009).

2.3.3. Comparative statics and numerical simulation

The solution to the second-stage problem is the best response function determined by the condition (2), which varies according to the parameters (r, k) as well as the unit cost of suppression (W_S) and a given level of pre-suppression (P). As shown by the best response curve in Figure 2.4.1, the two components of the fire program can display strategic complementarity. As pre-suppression effort increases, the incident manager increases their use of suppression, but at a decreasing rate. This result reflects the increased marginal productivity of suppression that is associated with rising applications of pre-suppression effort. Notice also in Figure 2.4.1 that there is a positive shift of the best-response function associated with rising levels of an incident manager's risk aversion. With CARA utility, this also indicates that suppression effort increases when the incident manager's tolerance for downside risks is lower.

Figure 2.4.1 - Incident Manager Best Response Function

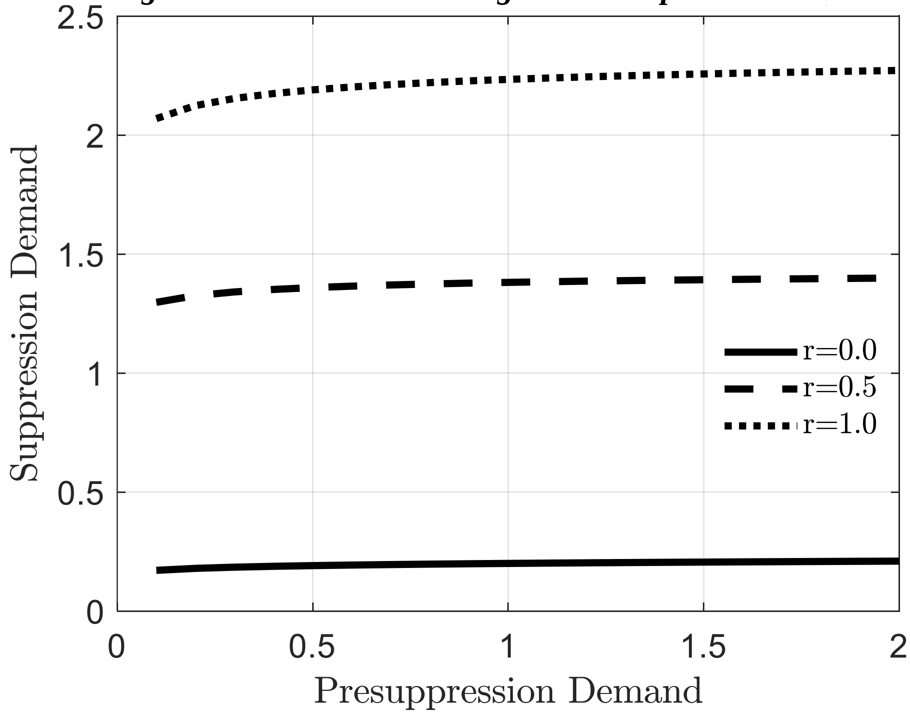


Figure 2.4.2 - Fraction of Fire Program Expenditures Devoted to Suppression

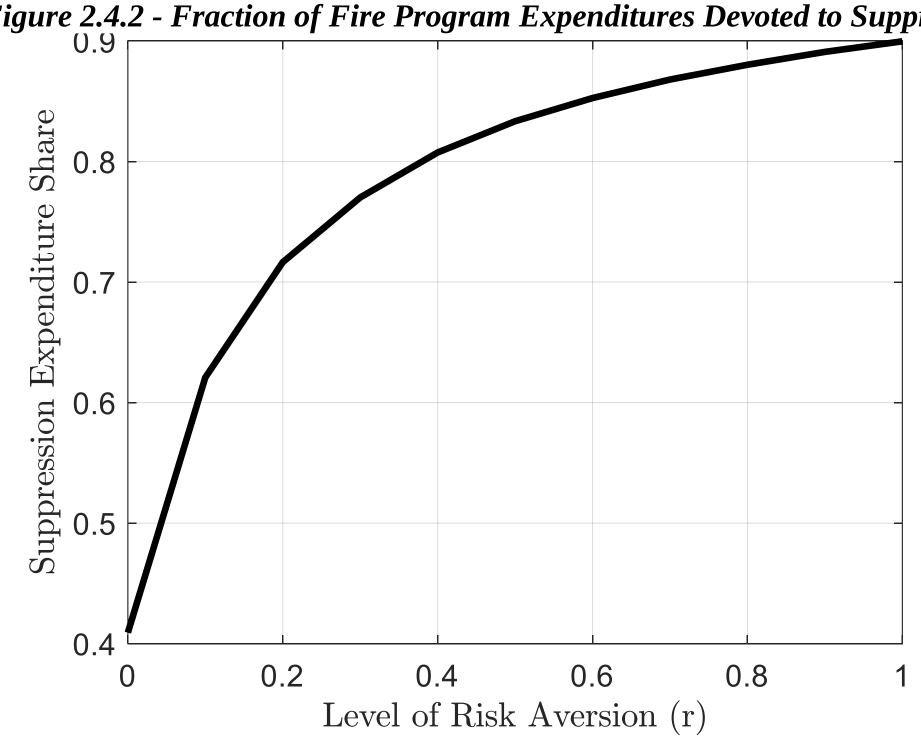


Figure 2.4.2 shows that suppression's share of the organization's overall expenditures increase as risk aversion and aversion to downside risks increases. The result of a positive slope of the suppression expenditure share curve over ranges of r holds in either of two cases presented in part c of Proposition 1 $\left(\frac{\partial P}{\partial r} \gtreqless 0\right)$. This illustrates how a greater proportion of fire program funding is allocated towards suppression as the incident manager displays greater risk aversion and a lower tolerance to downside risk. The increase in suppression's expenditure share over increasing r thus occurs both when P is decreasing in r (Figure 2.5.1) and when P is also increasing in r but at a slower rate than S (Figure 2.5.2). In both cases, the effect of increasing risk aversion has a smaller impact on the demand for presuppression relative to the unified case, where the level of risk aversion reflects that of the representative decision-maker for the fire management organization (Figure 2.5.3). In the unified model, greater levels of risk aversion have the effect of increasing presuppression by a larger amount than in the sequential model where the administrator displays a strategic response to increases in the incident manager's level of risk aversion.

Figure 2.5.1 - Fire management effort over incident manager risk aversion ($\sigma_\theta = 2.65$)

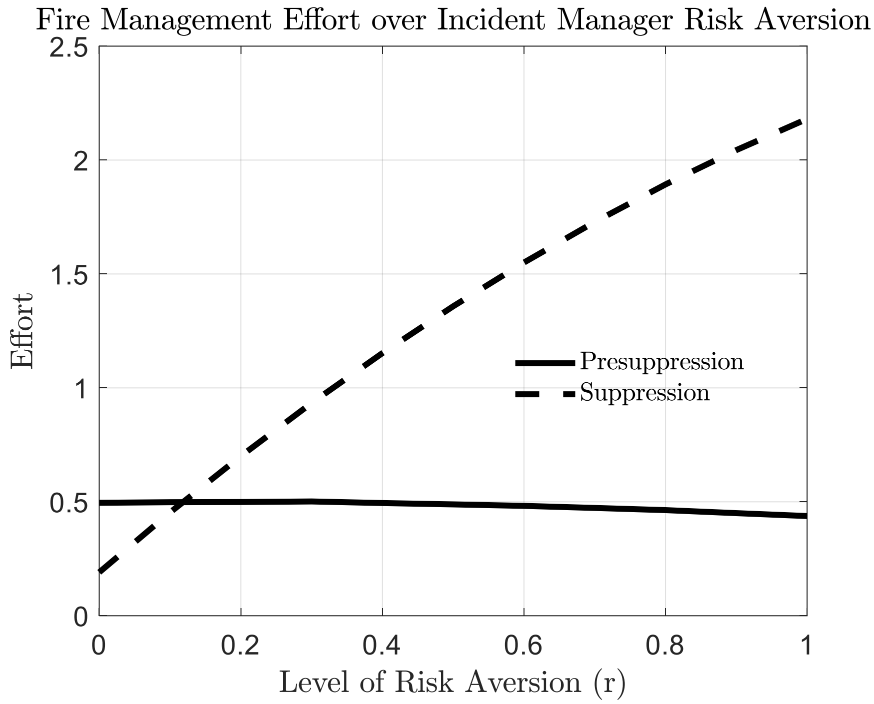


Figure 2.5.2 - Fire management effort over incident manager risk aversion ($\sigma_\theta = 2.925$)

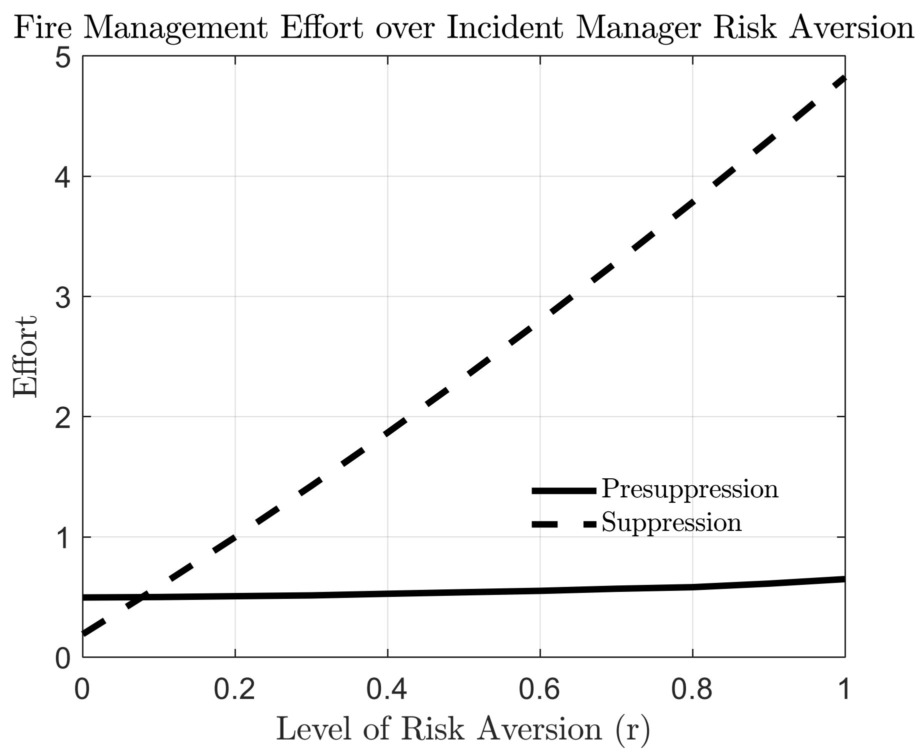
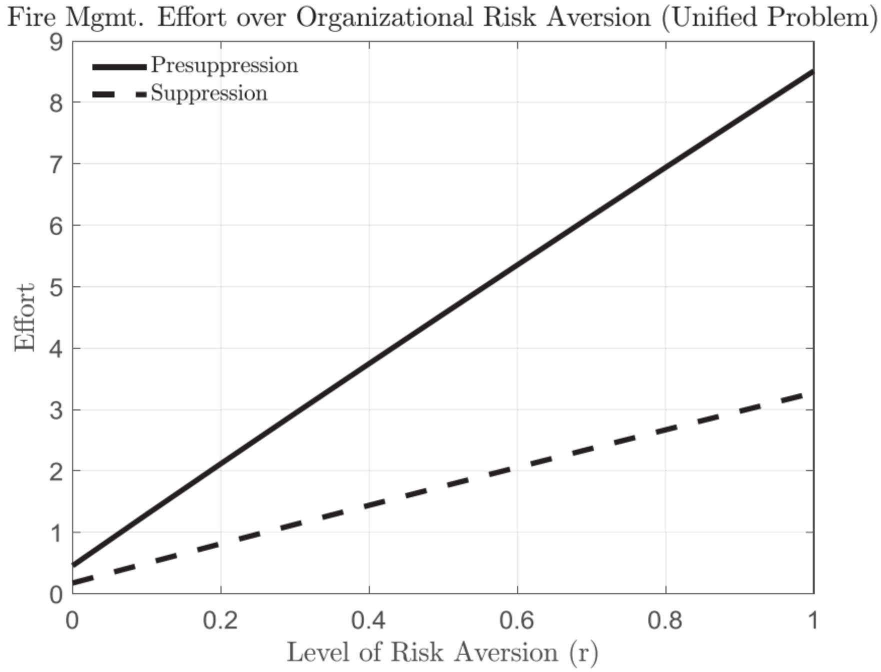


Figure 2.5.3 - Fire management effort over organization's risk aversion (unified problem)



Notice that when the incident commander's risk aversion is increasing, suppression effort is increasing slower in Figure 2.5.1 than in Figures 3.5.2. One explanation for this difference between figures 2.5.1 and 2.5.2 is that presuppression use is decreasing in risk aversion, hence in effect slowing down the increase in suppression expenditures (strategic effect). In Figure 2.5.3 the increase in suppression expenditures is faster than in Figures 3.5.1 and 3.5.2 since the presuppression expenditures also increase rapidly in the unified case when risk aversion increases. Under the given price ratio, we can also see that the share of effort in suppression is rising in the level of risk aversion at a faster rate in the sequential budgeting problem (Figures 2.5.1 and 2.5.2) when compared to the unified budgeting problem (Figure 2.5.3). Finally, notice that as the risk aversion parameter becomes smaller, the effort levels in all figures converge to the risk neutral case (the point where the curves intersect the y-axis). The expenditure allocation in the risk neutral case of Figure 2.5.3 corresponds to the socially efficient solution, as defined by a risk neutral social planner in a unified model.

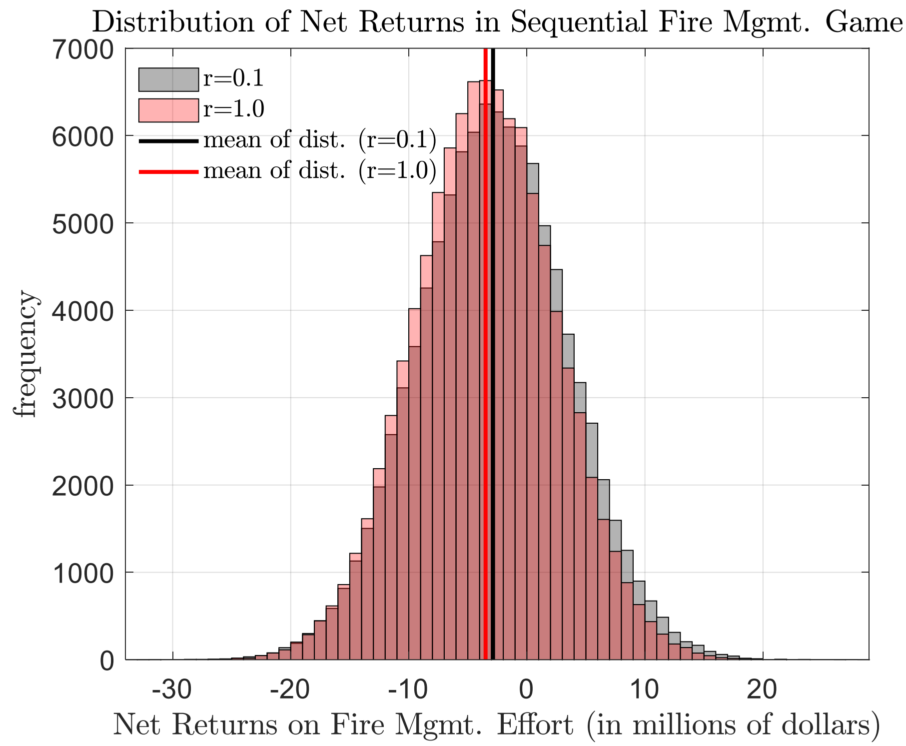
The next subsection will use these derived demand functions to calculate the additive components of the objective function in the first stage of the sequential game under different draws of the random variable θ using alternative assumptions about the symmetry of its distribution. This allows for a comparison of net return distributions to assess risk-return tradeoffs and program effectiveness when incident managers display non-neutral attitudes towards risk.

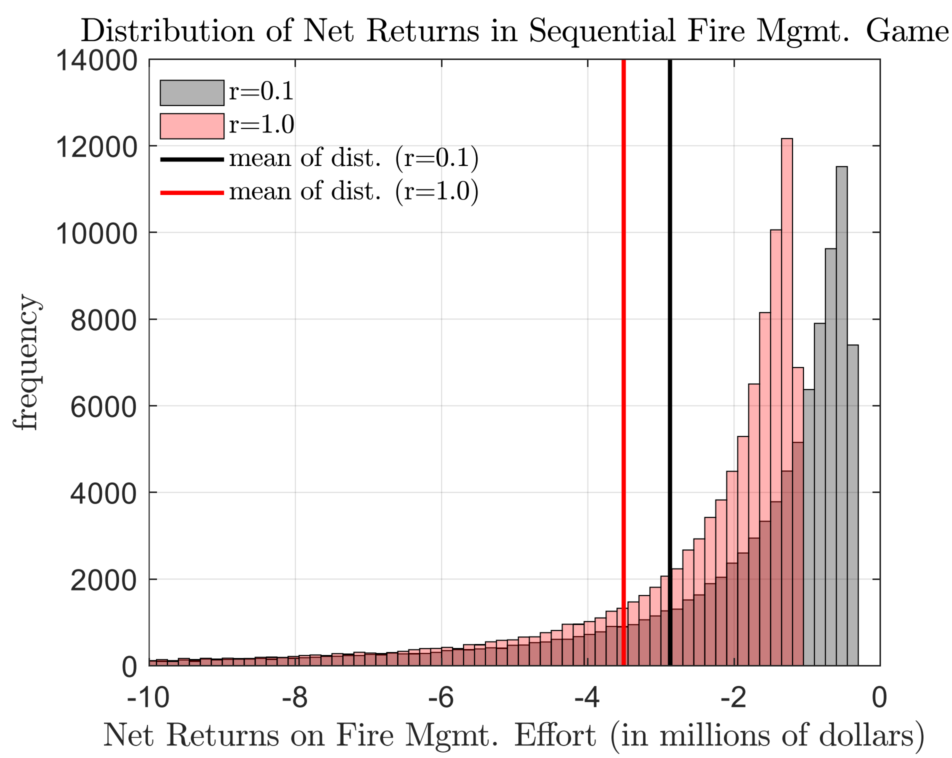
2.3.4. Numerical simulation

Given a constant variance of the multiplicative risk term (θ), 100,000 draws of random returns were generated and assessed under differing levels of the parameters describing the risk attitudes of incident commanders under both CARA and DARA utility functions.[12] Assessing the distribution of overall social returns from a fire program with a risk averse incident manager facing normally distributed returns yields a risk-return tradeoff similar to the one shown in Figure 2.6 (top). It is apparent in Figure 2.6 (top) that the effect of a risk averse incident manager yields lower overall returns, on average, but yields more certain returns. When the second-stage decision-maker in the organization seeks to avoid a wide variance of negative outcomes, they can increase their use of suppression effort to create more certainty. The strategic response of the administrator in the first stage is to anticipate this aversion to uncertainty and cut back on the use of pre-suppression effort. The overall effect of an incident manager's risk aversion is a lower net social returns, on average.

[12] Simulations with DARA utility are conducted using $u(V) = \ln V$, implying that the incident manager's certainty equivalent is: $\mu - \frac{1}{2\mu}\nu + \frac{1}{3\mu^2}\varphi - W_S S$.

Figure 2.6 - Distribution of Net Returns in Sequential Fire Mgmt. Game (CARA)

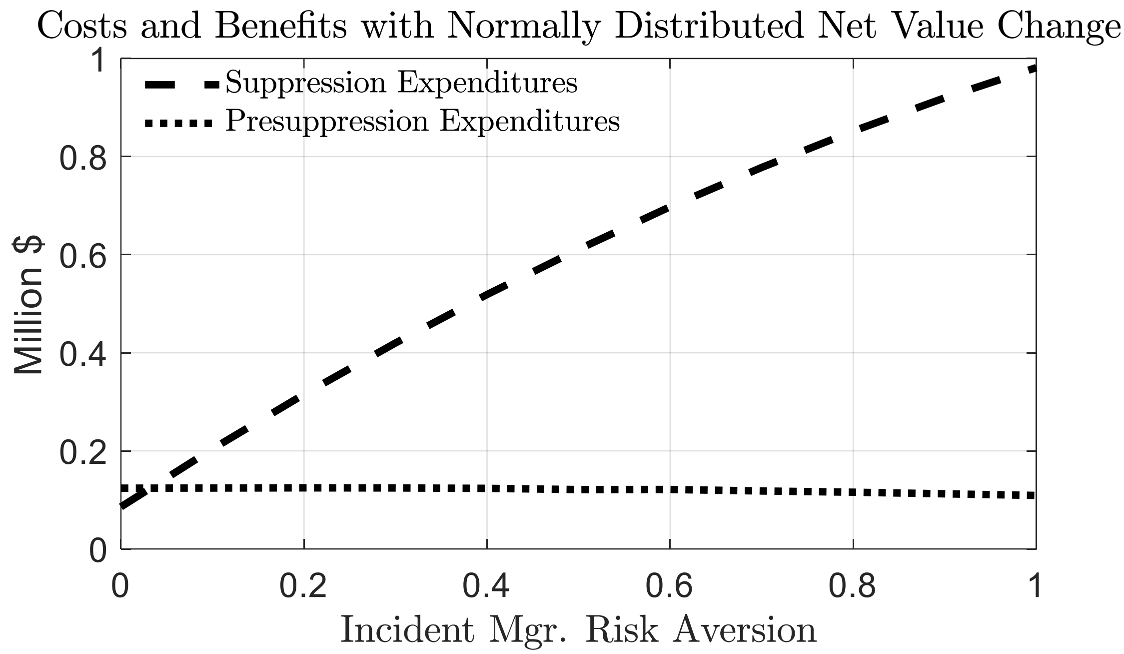


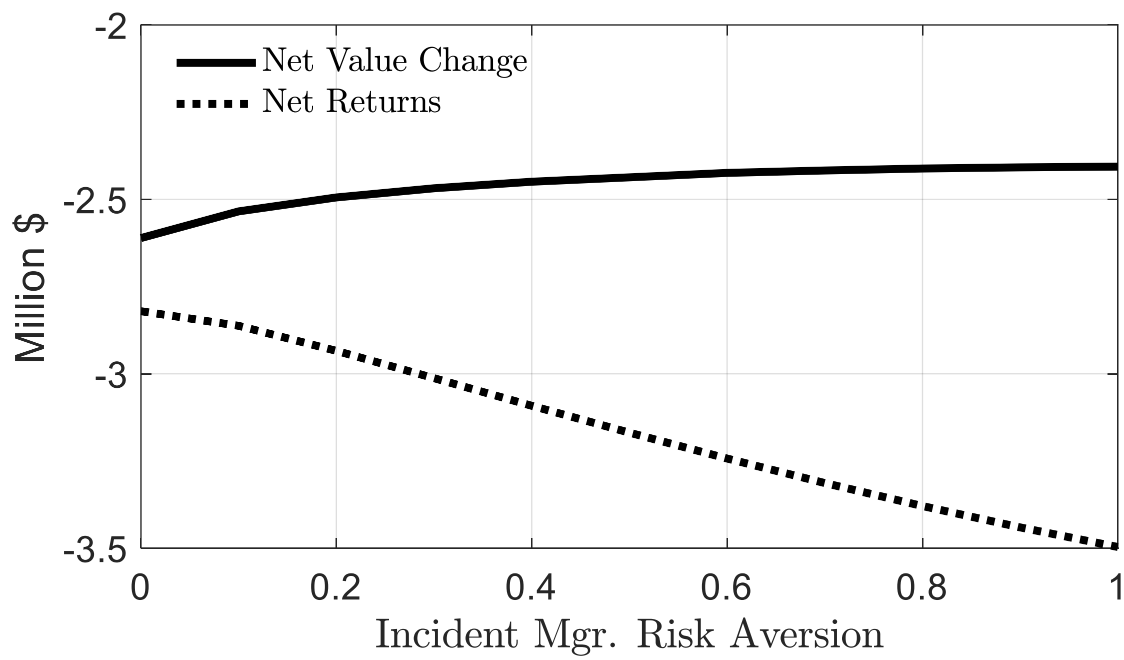


With an assumption of non-symmetrically distributed returns (which may follow, for example, a log-normal distribution) and a constant level of risk aversion, the influence of skewness will affect the incident manager's risk premium and the resulting allocation of fire management effort. Figure 2.6 (bottom) displays a case where an incident manager's risk aversion can also characterize aversion to third moment characteristics of the return distribution. Such aversion to downside risks can shift the net return distribution such that, on average, social returns generated by the fire management organization are lower but the skewness of returns is greater (i.e. less negative skew).

Figure 2.7 (top) shows the suppression and presuppression expenditures separately as a function of the risk aversion parameter, using the same distributional form as in Figure 2.6 (top). The responses in the two expenditure classes are qualitatively similar to Figure 2.5.1, with suppression funding increasing while presuppression spending slightly decreasing. Figure 2.7 (bottom) shows how the expected net value change is increasing in the risk aversion parameter while the overall expected total program returns are decreasing due to increased proportions of spending devoted to suppression. The same pattern holds for cases of log-normally distributed net value change and when output productivities are equalized (not shown).

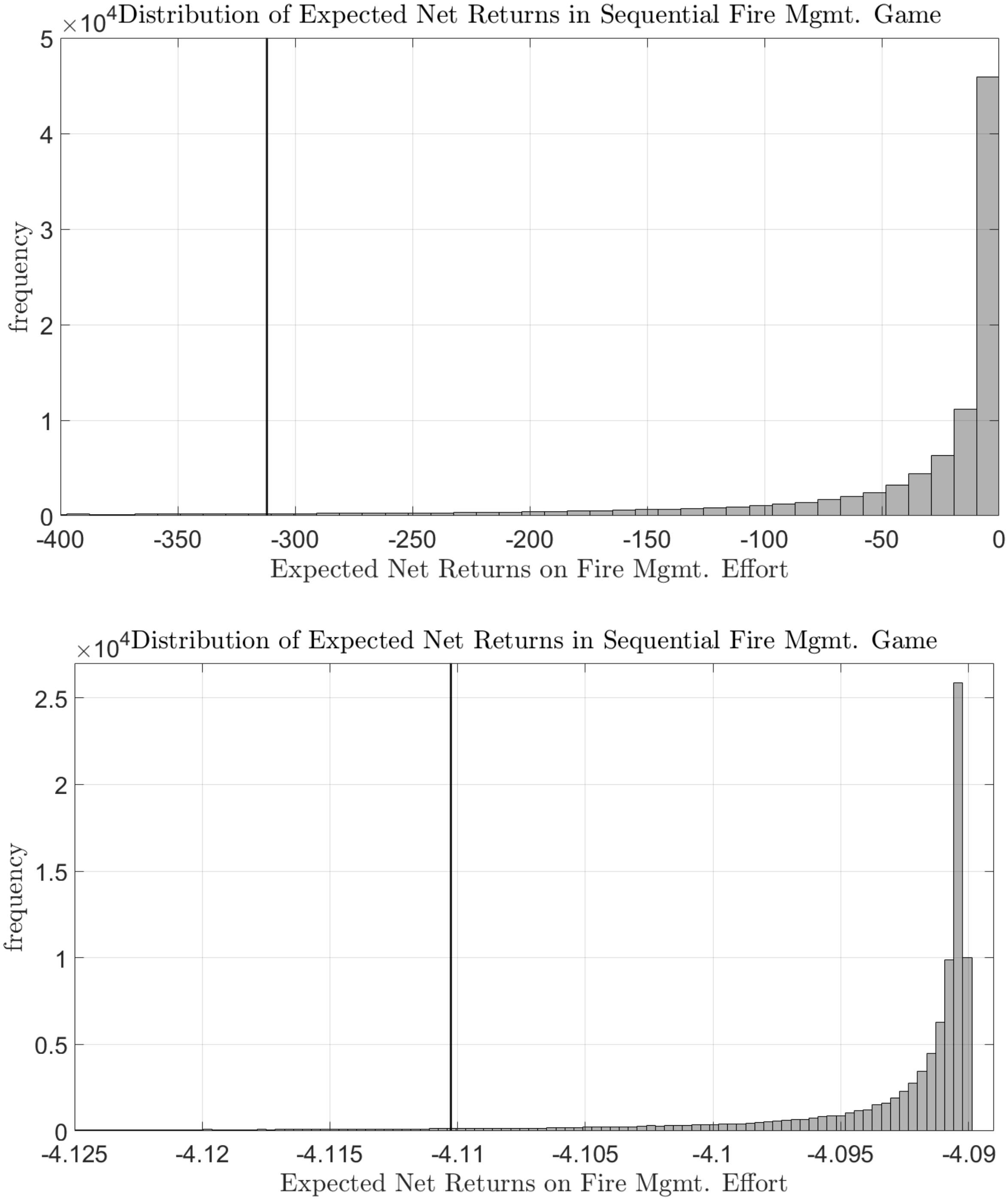
Figure 2.7 - Costs and Benefits with Normally Distributed Net Value Change





Similar effects can be shown for the case of DARA utility (Figures 2.8 (top) and 2.8 (bottom)). Since risk aversion is not a constant parameter with DARA, we vary the level of the parameter β instead. Parameter β impacts the joint marginal productivity of presuppression and suppression efforts (see Eq. 3.6). In Figure 2.8 (top), the marginal productivity is lower ($\beta = 2$), whereas in Figure 2.8 (bottom), it is higher ($\beta = 3.75$). With higher marginal productivity, the skewness of the net return distribution increases. An increase in the parameter β raises the expected net returns, lowers the variance of possible outcomes through risk aversion, and increases the skewness of the net return distribution through increases in the right-tailed skewness of V. Hence, improvements in the total productivity of fire management effort yields better outcomes in the sense that the left-tail (catastrophic) risks are reduced in likelihood.

Figure 2.8 - Distribution of Net Returns in Sequential Fire Management Game (DARA)



2.3.5. Discussion and Conclusion

Deviations of fire management allocations from the socially efficient allocation are often interpreted as a result of some form of decision bias or "satisficing" behavior (Taynor et al., 1990; Maguire and Albright, 2005; Wilson et al., 2011; Wibbenmeyer et al., 2013; Holmes and Calkin, 2013; Thompson et al., 2017). Satisficing refers to any decision-maker's acceptance of a suboptimal solution to their own decision problem when the computational or cognitive search cost required to find a globally optimal solution is too great given the time available to make a decision. Whereas a satisficing decision-maker may not know all of the parameters of the function that characterize their cost function or their cost of risk, a risk averse individual acts *as if* they know these parameters and requests suppression resources with this knowledge to maximize risk adjusted net benefits. The sequential model with uncertainty and risk averse incident managers is shown here to generate a similar shift in a fire program's expenditure shares as in the case where incident managers simply displace the costs or satisfice (Rossi and Kuusela, 2019). This result suggests that observed increases in suppression's share of fire management budgets can be interpreted to arise from either a rational response to uncertainty or from a display of bounded rationality whereby some acceptable level of suppression costs above the true level is admissible in a complex, time-pressured decision environment. One or more non-neutral attitudes towards risk in the second stage decision problem of the sequential model can impact suppression's expenditure allocation by raising the demand for suppression and indirectly influencing the administrator's choice of pre-suppression effort. This theoretical result suggests that further empirical modeling is needed to determine if manager-level differences in suppression demand are due to different types of risk attitudes, and to measure the impact of risk attitudes on observed budget allocations. Knowledge of this information may be useful for informing future budgeting or contracting decisions.

The potential implications of fragmented budgeting in the microeconomic model arise through the strategic interaction in the decision structure by introducing a leader and a follower with different objectives. The sequential equilibrium in this paper is used to show that risk aversion can potentially have an opposite effect on suppression expenditures and presuppression expenditures in the fire program, in contrast to a unified fire budgeting program where the representative decision-maker of the organization is either risk neutral (the benchmark case) or risk averse. Because of strategic interaction in the fragmented budgeting outcome, pre-suppression effort can actually be decreasing in higher levels of risk aversion while suppression effort increases. Since we do not know much about the risk preferences of administrators and it is convention to formulate public fire budgeting problems using a risk neutral planner (Rideout et al., 2008), our view is that a risk neutral first stage and a risk-averse second stage depicts the current institutional structure of wildfire program budgeting and reflects recent empirical literature. The sequential structure of the model thus provides a useful theory for explaining why pre-suppression budgets may be stagnant or falling as suppression budgets are rising.

To simplify the analysis, our model assumes two homogenous inputs. In reality, both inputs would be better modeled as multidimensional vectors that represent a rich set of alternatives that managers in fire organizations have access to (such as hand crews, strike team leaders, bull dozers, fire engines, and air tankers). There are three alternative strategies to a "full suppression" response, including strategies that seek to "confine" a fire to a defined area, strategies that engage in "point protection" of homes or other values at risk, and strategies that only "monitor" the behavior of a burning wildfire. Our model suggests that incident managers are more likely to engage in aggressive suppression strategies like "full suppression" when fires occur in close proximity to values at risk (e.g. WUI) where the effect of more aggressive strategies increases the skewness of the benefit distribution (or equivalently decreases the skewness of the NVC distribution). At greater distances from these areas, our model suggests that more aggressive suppression choices limit the upside potential for wildfires to generate resource benefits. Our model predicts that in such cases, “wildfire monitoring” strategies are more likely adopted by the representative downside risk averse incident manager. Testing this hypothesis with statistical methods seems to be an important direction for future research.

One important extension of the sequential model which is not presented here may be the effect of uncertainty over critical parameter values in the second-stage problem. This extension would relax the assumption of complete information in the sequential game and allow the administrator in the first stage to maintain or develop some expectation about the incident manager’s risk attitudes. This extension would lead naturally to a related discussion about optimal mechanism design. In cases where uncertainty over characteristics of the incident manager are constraining the fire program from attaining a socially efficient allocation of fire management effort, an optimally designed contract can be implemented between the administrator and the incident manager to ensure compliance with the overall program objective to maximize expected net social returns.

The microeconomic framework presented in this paper represents a type of natural disaster management problem where budgeting for program components is fragmented. While the framework is potentially generalizable, precaution should be taken when applying the sequential wildfire economics model to other disaster management settings. Specifically, the model may not be generalizable to a circumstance where fragmented budgeting does not persist across precautionary and reactionary disaster management efforts. Fragmented budgeting can create efficiency problems by treating public budgets as common pool resources (Von Hagen, 2007; Raudla, 2014), but they may not be present in all fiscal policy settings. Other agencies may also have different procedures for budgeting (they may not contract out any portion of their discretionary appropriations to incident management nor may they have access to emergency funding sources when initial appropriations are exhausted). It is also possible that other contracted incident managers display less risk aversion or are tied to a contract that dictates a longer-term management perspective. In these cases, it is less likely that the objectives of the public agency and the contracted incident manager diverge from one another. These special circumstances (and maybe others) would be important considerations before any attempt is made to generalize the microeconomic model presented in this paper.

The sequential model can, however, provide several important explanations for current patterns of observed fire management behavior. The model suggests that when fires occur near high-valued developments or across fire-sensitive ecosystems, rational incident management under uncertainty entails a full suppression strategy and a greater demand for suppression effort. The consequence is lower overall returns as agency demand for pre-suppression effort falls to accommodate the larger expenditures on suppression. Alternatively, fires burning farther from high-valued developments or across fire-dependent ecosystems can induce an alternative type of suppression response. In these cases, rational incident management under uncertainty may involve allowing fires to burn to achieve resource benefits. In both cases, management choices can be driven by the risk averse attitudes of incident managers. It is this aversion to risk that can cause incident managers to demand greater suppression effort when downside exposure is relatively larger (payoffs skewed left) and reduce suppression effort when upside exposure is relatively larger (payoffs are skewed right).

The sequential framework also provides several insights for the design of fire management policy and an explanation for the tendency for suppression to encompass greater proportions of land management budgets. Specifically, the sequential model suggests that when incident managers and land management agencies do not face incentives to budget for pre-suppression and suppression simultaneously, then the resulting allocation of fire management effort will be inefficient, on average, when one or more managers in the organization are averse to risk. This stresses an important role for cooperation between agency administrators and incident managers in the decision-making process of the fire management organization if risk is of no concern and the goal is to maximize expected net social value of the program over time. Currently, the agency objectives are already stressing the importance of further increasing cooperation so that incident management is more aligned with overall agency goals (Jewell and Vilsack, 2014). While our modeling results provide useful theoretical support for such planning activities, the actual determination of the socially efficient mix of presuppression and suppression expenditures is an empirical question and beyond the scope of the current paper.

Our results suggest that if fragmented budgeting persists and the risk attitudes of managers are not identical across different stages of the budgeting decision, then the “longrun” social optimum will not be attainable. When risk attitudes are not aligned, then the objectives of a public fire management agency tasked with a “long-run” policy objective are likely to diverge from those of a contracted incident manager displaying risk aversion during the “short run” management of an unplanned fire event. This short-run structure of the second stage problem is driven by the property that pre-suppression effort is held fixed (since annual budgets are pre-determined) while suppression effort is allowed to vary when additional reserve funding is released throughout the fiscal year. Enabling the use of reserve funding from the Federal

Emergency Management Agency, or by appropriating additional reserve funds as part of the recently passed Consolidated Appropriations Act (H.R. 1625), is unlikely to re-align these objectives and may cause them to deviate further if risk attitudes are not aligned across stages of the budgeting decision.

Appendix A: Proof of Proposition 1

Part a)

The total derivative of the first-order condition (2) (while holding the level of pre-suppression constant), yields:

$$\frac{\partial S}{\partial r}\left[\frac{\partial^2\mu}{\partial S^2}-\frac{r}{2}\left(\frac{\partial^2\nu}{\partial S^2}\right)+\frac{r^2}{6}\left(\frac{\partial^2\varphi}{\partial S^2}\right)\right]-\frac{1}{2}\left(\frac{\partial\nu}{\partial S}\right)+\frac{r}{3}\left(\frac{\partial\varphi}{\partial S}\right)=0.$$

(A.1)

Rearranging yields the partial effect of interest:

$$\frac{\partial S}{\partial r}=\frac{3\left(\frac{\partial\nu}{\partial S}\right)-2r\left(\frac{\partial\varphi}{\partial S}\right)}{6\left[\frac{\partial^2\mu}{\partial S^2}-\frac{r}{2}\left(\frac{\partial^2\nu}{\partial S^2}\right)+\frac{r^2}{6}\left(\frac{\partial^2\varphi}{\partial S^2}\right)\right]}.$$

(A.2)

The denominator of (A.2) is a positive multiple of the second-order partial of incident manager's objective and is negative by assumption of a maximum of (1). The sign of $\frac{\partial S}{\partial r}$ thus depends on the relative magnitude of the partial effects in the numerator of (A.2). We have assumed that $\frac{\partial \nu}{\partial S}<0$, thus (A.2) is unambiguously positive whenever $\left(\frac{\partial\varphi}{\partial S}\right)>0$. However, when $\left(\frac{\partial\varphi}{\partial S}\right)<0$,the sign of $\frac{\partial S}{\partial r}$ will still be positive whenever $2r\left(\frac{\partial\varphi}{\partial S}\right)>\left|3\left(\frac{\partial\nu}{\partial S}\right)\right|$ but will be negative if $2r\left(\frac{\partial\varphi}{\partial S}\right)<\left|3\left(\frac{\partial\nu}{\partial S}\right)\right|$.

Part b)

The effect of pre-suppression on suppression response is determined by

$$\frac{\partial S}{\partial P}=-\frac{\frac{\partial^2\mu}{\partial S\partial P}-\frac{r}{2}\left(\frac{\partial^2\nu}{\partial S\partial P}\right)+\frac{r}{6}\left(\frac{\partial^2\varphi}{\partial S\partial P}\right)}{\frac{\partial^2\mu}{\partial S^2}-\frac{r}{2}\left(\frac{\partial^2\nu}{\partial S^2}\right)+\frac{r^2}{6}\left(\frac{\partial^2\varphi}{\partial S^2}\right)}.$$

(A.3)

The denominator is negative by the assumption that the second order condition holds. Hence, if the numerator is positive, then the sign of the effect is positive.

Part c)

The pre-suppression stage first order condition is

$$\frac{\partial\mu}{\partial P}+\frac{\partial\mu}{\partial S}\left(\frac{\partial S}{\partial P}\right)-W_P-W_S\left(\frac{\partial S}{\partial P}\right)=0,$$

where $\mu = E[V(P,S,\theta)]$ and $S = S(P,W_S,r,\boldsymbol{\omega})$.

The effect of risk aversion parameter on pre-suppression can then be determined by the expression:

$$\frac{\partial P}{\partial r}=-\frac{\frac{\partial S}{\partial r}\left[\frac{\partial^2\mu}{\partial P\partial S}+\frac{\partial^2\mu}{\partial S^2}\left(\frac{\partial S}{\partial P}\right)\right]+\left(\frac{\partial^2 S}{\partial P\partial r}\right)\left[\frac{\partial\mu}{\partial S}-W_S\right]}{\frac{\partial^2\mu}{\partial P^2}+\left[2\left(\frac{\partial^2\mu}{\partial P\partial S}\right)+\frac{\partial^2\mu}{\partial S^2}\left(\frac{\partial S}{\partial P}\right)\right]\frac{\partial S}{\partial P}+\left(\frac{\partial^2 S}{\partial P^2}\right)\left[\frac{\partial\mu}{\partial S}-W_S\right]}$$

(A.4)

The denominator is the second-order condition of the first-stage problem, which is negative by assumption. Hence when the numerator is positive, the effect of risk aversion on pre-suppression is positive. Suppose that we allow $2r\left(\frac{\partial\varphi}{\partial S}\right)>\left|3\left(\frac{\partial v}{\partial S}\right)\right|$ so that $\frac{\partial S}{\partial r}>0$ and we let $\left(\frac{\partial S}{\partial P}\right)>0$ to reflect complementarity. Then the numerator of (A.4) will be positive when either:

$$\frac{\partial^2\mu}{\partial P\partial S}>\frac{\partial^2\mu}{\partial S^2}\left(\frac{\partial S}{\partial P}\right)\text{ and }\frac{\partial\mu}{\partial S}>W_S$$

(A.5)

or

$$\frac{\partial^2\mu}{\partial P\partial S}>\frac{\partial^2\mu}{\partial S^2}\left(\frac{\partial S}{\partial P}\right)\text{ and }\frac{\partial\mu}{\partial S}<W_S\text{, but }\left|\frac{\partial^2\mu}{\partial P\partial S}-\frac{\partial^2\mu}{\partial S^2}\left(\frac{\partial S}{\partial P}\right)\right|>\left|\frac{\partial\mu}{\partial S}-W_S\right|$$

(A.6)

or

$$\frac{\partial^2\mu}{\partial P\partial S} < \frac{\partial^2\mu}{\partial S^2}\left(\frac{\partial S}{\partial P}\right) \text{ and } \frac{\partial\mu}{\partial S} > W_S, \text{ but } \left|\frac{\partial^2\mu}{\partial P\partial S} - \frac{\partial^2\mu}{\partial S^2}\left(\frac{\partial S}{\partial P}\right)\right| < \left|\frac{\partial\mu}{\partial S} - W_S\right| \tag{A.7}$$

When the numerator is negative, as is true whenever any of the conditions (A.5) to (A.7) are violated, then the partial effect $\frac{\partial P}{\partial r}$ is negative. ■

Appendix B: Proof of Proposition 2

Assume a symmetric distribution around the mean value (i.e. no skewness). The unified problem can then be written as

$$\max_{P,S}\left\{\mu-\frac{\rho}{2}\nu-W_PP-W_SS\right\}. \qquad (B.1)$$

We will use subscripts to denote partial derivatives (but W_P and W_S are still constant unit prices). The F.O.C. for the unified problem are:

$$\mu_P-\frac{\rho}{2}\nu_P-W_P=0$$

$$\mu_S-\frac{\rho}{2}\nu_S-W_S=0. \qquad (B.2)$$

Notice that in each condition, since we assume both $\nu_P<0$ and $\nu_S<0$, increasing levels of overall risk aversion in the organization, ρ, will lower the effective marginal cost of fire management effort. By totally differentiating (B.2) w.r.t ρ, we arrive at the following comparative statics:

$$P_\rho^*=\frac{\frac{1}{2}\nu_{SS}\left(\mu_{PS}-\frac{\rho}{2}\nu_{PS}\right)-\frac{1}{2}\nu_{PP}\left(\mu_{SS}-\frac{\rho}{2}\nu_{SS}\right)}{\left(\mu_{PP}-\frac{\rho}{2}\nu_{PP}\right)\left(\mu_{SS}-\frac{\rho}{2}\nu_{SS}\right)-\left[\mu_{PS}-\frac{\rho}{2}\nu_{PS}\right]^2}$$

$$S_\rho^*=\frac{\frac{1}{2}\nu_{PP}\left(\mu_{SP}-\frac{\rho}{2}\nu_{SP}\right)-\frac{1}{2}\nu_{SS}\left(\mu_{PP}-\frac{\rho}{2}\nu_{PP}\right)}{\left(\mu_{PP}-\frac{\rho}{2}\nu_{PP}\right)\left(\mu_{SS}-\frac{\rho}{2}\nu_{SS}\right)-\left[\mu_{PS}-\frac{\rho}{2}\nu_{PS}\right]^2} \qquad (B.3)$$

The denominators in (B.3) must be positive since we assume the presence of an interior solution. Hence, both input responses will be positive if $\nu_{SS}>0,\nu_{PP}>0,\nu_{PS}<0$ and $\mu_{PP}<0,\mu_{SS}<0,\mu_{PS}>0$. The latter set of assumptions pertains to the NVC function. The first set of assumptions states that both pre-suppression and suppression decrease the variance at a decreasing rate and that the two efforts are jointly productive in decreasing the variance.

Appendix C: Show expressions for higher order moments of the net return distribution

Part a)

The variance of net value change is as expressed in equation (8). With a fire management technology of the Cobb-Douglas form and a multiplicative risk parameter with mean 1, we can *find an expression for the second central moment of the return distribution*. We seek the variance of $V(P, S, \theta)$

$$\nu = \mathrm{var}\big(\theta(\beta P^{\gamma_1} S^{\gamma_2} - \alpha)\big)$$

Note that the production relation $\beta P^{\gamma_1} S^{\gamma_2} - \alpha$ is deterministic while the random variable θ is the multiplicative risk parameter with mean $\mu_\theta = 1$ and unspecified variance σ_θ^2. Using a well-known property of the variance operator, we can rewrite the above as:

$$\nu = \mathrm{var}(\theta)(\beta P^{\gamma_1} S^{\gamma_2} - \alpha)^2$$

Or:

$$\nu = \{\mathrm{E}[\theta^2] - (E[\theta])^2\}(\beta P^{\gamma_1} S^{\gamma_2} - \alpha)^2$$

Notice that $(E[\theta])^2 = 1$ and that *the second central moment of* θ is $\mathrm{E}[\theta^2] = \sigma_\theta^2$. Therefore, the variance of net returns is a deterministic function of the standard deviation of θ:

$$\nu = (\sigma_\theta^2 - 1)(\beta P^{\gamma_1} S^{\gamma_2} - \alpha)^2$$

Which is equation (8).

Part b)

The skewness of net value change is as expressed in equation (9). With a fire management technology of the Cobb-Douglas form and a multiplicative risk parameter with mean 1, we can find an expression for the third central moment of the return distribution. As derived, the skewness of $V(P, S, \theta)$ is defined as:

$$\varphi = \text{skew}\big(\theta(\beta P^{\gamma_1} S^{\gamma_2} - \alpha)\big)$$

Separating out the deterministic production relationship gives:

$$\varphi = \text{skew}(\theta)(\beta P^{\gamma_1} S^{\gamma_2} - \alpha)^3$$

Or:

$$\varphi = \text{E}[(\theta - \mu_\theta)^3](\beta P^{\gamma_1} S^{\gamma_2} - \alpha)^3$$

Factor and simplify:

$$\varphi = \text{E}[(\theta - \mu_\theta)(\theta - \mu_\theta)(\theta - \mu_\theta)](\beta P^{\gamma_1} S^{\gamma_2} - \alpha)^3$$

$$\varphi = \{\text{E}[\theta^3] - 3\text{E}[\theta^2] + 3\text{E}[\theta] - 1\}\,(\beta P^{\gamma_1} S^{\gamma_2} - \alpha)^3$$

Note that the *first central moment of* θ is $\text{E}[\theta] = 1$. The *second central moment of* θ is $\text{E}[\theta^2] = \sigma_\theta^2$. The *third central moment of* θ is $\text{E}[\theta^3] = \sigma_\theta^3$. Therefore, the skewness of net returns is a deterministic function of the standard deviation of θ and the skewness of θ:

$$\varphi = \left\{\sigma_\theta^3 - 3\sigma_\theta^2 + 2\right\}(\beta P^{\gamma_1} S^{\gamma_2} - \alpha)^3$$

Which is equation (9). Notice that with a symmetric distribution of the random parameter θ centered around a mean of 1, we have both $\sigma_\theta^3 = 0$ and $\sigma_\theta^2 = 2/3$, so that $\varphi = 0$. This case can be true for a normal density function $f(\theta)$.

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CHAPTER 3: ECONOMICS OF CARBON AND TIMBER MANAGEMENT UNDER TAX-FINANCED INVESTMENTS IN WILDFIRE RISK MITIGATION

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3.1. Introduction

Forests in the Pacific Northwest are highly productive both as sources of timber supply and for their potential to capture and store carbon (Kline et al., 2016; Diaz et al., 2018). Some of the most productive areas are privately owned, either by industry or family owners. Emerging markets for carbon offset credits are one mechanism that landowners in this region can utilize to receive compensation for carbon storage (Kline et al., 2009; Latta et al., 2016). For example, landowners in Oregon are currently eligible to sell offset credits as part of California's regional cap-and-trade program. Several projects have recently been approved, such as Green Diamond's carbon offset project which covers 600,000 acres across southern Oregon.[13] Offset projects in the state are currently underway in Clatsop, Multnomah, Jefferson, and Klamath counties (Burtaw et al., 2019).

There is growing interest in enrolling more forests in the Pacific Northwest into a carbon offset credit program (Latta et al. 2016). Landowners can enroll their land into an offset program through "Improved Forest Management" actions which can entail a commitment to increase forest rotation ages beyond the length they would have planned in the absence of an offset program (CARB, 2011; ORS, 2020). In return, landowners are eligible to sell offset credits to regulated entities in a regional offset auction, such as the California-Quebec joint auction administered by the California Air Resources Board.

However, these same forests are also subject to a risk of wildfire disturbances which may lead to unintentional releases of carbon and losses in carbon storage (Law and Waring, 2015). From 1980 to 2019, approximately 17% of total burned area across Oregon and Washington has affected private forestland, compared to 28% in 2020 alone (Campbell Global, 2020). The Labor

[13] https://www.greendiamond.com/recreation/oregon-lands/

Day Fires of 2020 impacted over one million acres of forestland in Western Oregon, of which about 40% was estimated to be private timberland. Such disturbances and the increasing risk of disturbances may also jeopardize the effectiveness of carbon offset programs that demand longer rotations (Kuusela and Lintunen, 2020).

To mitigate wildfire risk exposure, both federal and state forestry agencies manage wildfire ignitions and spread patterns at the landscape scale through annual investments in wildfire suppression programs and projects that remove hazardous fuels (Crowley et al., 2009; Lueck and Yoder, 2015). Both suppression and pre-fire hazardous fuels management undertaken by public agencies have been modeled as inputs which serve to reduce parcel-level burn probability (Rideout et al., 2008). Also, fuels management activities undertaken by private landowners at the stand level act as a fire prevention measure that can decrease the frequency of disturbances experienced by the stand and the neighboring stands (Amacher et al., 2005; Konoshima et al., 2008). Research has also found that increases in suppression program budgets can significantly reduce parcel-level fire frequency by improving initial attack response and the successful containment of large fires (Lee et al., 2013). Higher initial attack success rates can lower parcel-level burn probability estimates via reductions in crew response times (Rideout et al., 2016; Reimer et al., 2019).[14] Therefore, effective risk mitigation efforts on private lands encompass both public suppression investments and private or public fuels management, both of which serve to decrease the frequency of disturbances experienced by an acre of private forestland.

[14] Maintaining an "initial attack success" rate above 98 percent is a stated federal policy objective (USFS, 2007). In fiscal year 2018, 97 percent of forest fires on U.S. Forest Service land were contained before reaching 300 acres in size (USFS, 2019). Initial attack success is also a stated policy objective of state forestry agencies. In 2017, the Oregon Department of Forestry extinguished 94 percent of wildfires before they reached 10 acres in size (ODF, 2017).

Federal land management programs actively fund both suppression and hazardous fuels management programs on federal lands (Gebert et al., 2008). However, at the state level, the main focus of wildfire management programs has traditionally been the suppression and containment of fires on private forestlands (ODF, 2021). For example, the Oregon Department of Forestry (ODF) is responsible for suppressing wildfires on private lands in Oregon. Its expenditures on fire suppression activities are financed in part through forest taxes which include both unit taxes on harvest volume and acre-based assessments. Additional appropriations come from Oregon's General Fund. In the 2021-2023 biennial budget, $191 million was appropriated toward the agency's fire protection program, 47.6 percent of which was allocated from the state's General Fund and 9.7 percent of which was provided through federal funding (ODF, 2021). The remaining 42.3 percent of the biennial allocation was raised through forest-based taxes, including emergency sources provided by the Oregon Forest Land Protection Fund and Landowner Assessed Fees (ODF, 2021). Given this funding structure, the risk of devastating wildfires on private lands depends partly on the level of taxes collected from private landowners since the tax receipts are used to fund fire preparedness and initial- and extended-attack suppression response. However, it is not well understood how such tax schemes that fund risk mitigation programs should be designed especially when potential carbon policies would at the same time incentivize longer rotations.

The purpose of our research is to analyze the optimal design of a state-level tax program that funds risk mitigation activities on private lands when the carbon stored in forests and wood products has value. Following the literature on the design of forest tax policy, we use a stand level model of an even-aged forest to investigate the effects of taxation (e.g. Koskela and Ollikainen, 2003; Amacher et al., 2009, Ch. 5). We restrict our attention to two tax instruments utilized in Oregon: 1) a unit tax on harvest (yield tax), and 2) an annual acre-based assessment. In our model, the social planner (a state agency) is modeled as a Stackelberg leader that commits to a time-invariant tax policy when deciding both tax rates and annual expenditures on risk mitigation.[15] In the second stage of the model, a private forestland owner responds with their choice of the optimal harvest rotation age. Following Koskela and Ollikainen (2003), we assume the existence of a steady-state, and so transitional dynamics of the optimal policy rule are ignored. A quantitative assessment of the optimal tax policy is conducted using a parameterized timber yield function for Western Oregon Douglas-fir (*Pseudotsuga menziesii*) and a production function that describes the transformation of risk mitigation expenditures into reductions in the fire arrival rate.

Prior research on stand-level carbon and timber management under disturbance risk has used the framework of a representative timberland owner to understand the interactions between fire risk management and carbon sequestration capacity (Daigneault et al., 2010). Daigneault et al. (2010) use a numerical dynamic programming model to show that the introduction of a carbon market can induce more frequent management of hazardous fuels on the forest stand in order to better secure older growth carbon revenues. By combining the optimal rotation models analyzed by Reed (1984) and van Kooten et al. (1995), Ekholm (2020) examines the impact wildfire risk on rotation choice when forest carbon has value. This leads to a model of multiple-use stand management subject to fire risk which is similar to the models analyzed by Englin et al. (2000) and which is based on the Faustmann approach to forest valuation (Samuelson 1976).

[15] The two-stage game-theoretic framework of the forest taxation problem in this paper further avoids “time inconsistency” problems that may be associated with a discretionary tax policy developed using optimal control theory (Kydland and Prescott, 1977).

In our study, we also use the optimal rotation framework presented by Ekholm (2020). However, we add the additional complication that the fire arrival rate is dependent on public investment in suppression and this investment is explicitly financed through forest taxation. This linkage between forest taxation and public investment in suppression occurs through an intertemporal public budget constraint but has not yet been considered in the forest taxation literature. In contrast to the model presented by Crowley et al. (2009), we model the planner's suppression expenditures as having an influence on the arrival rate of an acre of forestland rather than on the stand's salvage possibilities. This allows us to capture the effects of a reduction in spread probability that accompanies an annually active suppression program.

The impacts of different tax instruments on management choices have been studied in several papers using the optimal rotation framework (e.g. Klemperer, 1976; Chang, 1982; 1983; Amacher et al., 1991). The findings from these studies have made a general distinction between two categories of taxes: distortionary and neutral taxes. Neutral taxes (e.g. acre-based assessments) have no impact on the optimal decision made by the private landowner, whereas distortionary taxes (e.g. yield taxes) cause landowners to change management choices compared to the no-tax scenario. While knowing the responses in management choices, such as the rotation age, induced by taxes is useful, state agencies still need to know what instruments are best on efficiency grounds and what level of taxes should be set. Some of the important determinants of this problem are whether the government faces binding revenue constraints and whether the private landowners generate public goods valued by society (Amacher et al., 2009, Ch. 5).[16] In the absence of externalities, a government seeking to raise revenue from forest taxes should only

[16] Taxation schemes are said to be "first-best" if they are used align the decisions of the landowners with the socially optimal decisions. Additionally, if neutral taxes can be used to satisfy potential revenue constraints, the scheme is first-best. If neutral taxes are not available and distortionary taxes must be levied to meet an exogenous public revenue constraint, the tax scheme is said to be "second-best."

use neutral taxes as suggested by the Ramsey rule (Gamponia and Mendelsohn, 1987). However, when externalities are present together with revenue constraints, the government may need to also resort to the use of distortionary taxes (Koskela and Ollikainen, 2003).

Despite these well-established results on optimal forest taxation, there has been few attempts in the literature to understand the properties of first- and second-best taxation schemes on landowner management decisions and forestland values when disturbance risk is present. One exception is the work of Alvarez and Koskela (2007) who examine the effects of yield taxes and lump-sum taxation schemes on rotation length when landowners are risk neutral or risk averse in the presence of stochastic forest values. They find that these taxes raise the optimal harvesting threshold, leading to longer rotations, regardless of risk preferences. However, their research has left unaddressed the influence of a planner's provision of risk reduction and its impact on a private landowner's disturbance risk. Our results demonstrate that the presence of endogenous risk in the optimal forest tax problem has implications for the choice of the tax instrument. Namely, an endogenous fire risk can alter the optimal second-best tax policy depending on whether the benefits of carbon sequestration are internalized by private landowners or not.

We find that acre-based assessments are still neutral from the perspective of the landowner. However, when receipts from acre-based assessments are raised for the purpose of funding risk mitigation, they will indirectly influence rotation lengths. We also show that the landowner's inability to internalize the social benefits of carbon sequestration can lead the planner to instead prescribe harvest taxes in lieu of the acre-based assessment. However, the capacity for the harvest tax to serve as a corrective (Pigouvian) instrument is limited by its small impact on net stumpage value. When fire risk is present, but carbon sequestration benefits are internalized by the landowner, the acre-based assessment remains the preferred instrument and harvest taxes should be set to zero from a purely efficiency perspective. The optimal size of these taxes is sensitive to the carbon price, carbon storage parameters, and on the effectiveness of the planner's expenditures on risk mitigation in terms of its ability to reduce the frequency of fire disturbances experienced by a private landowner.

The remainder of this paper is organized as follows. In the next section, we develop a two-stage model where in the second stage, a landowner subject to wildfire risk and carbon values chooses the optimal rotation age. In the first stage, the planner optimizes the social welfare by choosing the levels of the tax instruments subject to a budget constraint that determines the feasible level of expenditures on risk reduction activities. Section 3 defines the model parameters used for the quantitative analysis of the model. Section 4 presents the results and Section 5 provides a discussion and conclusions.

3.2. Model

3.2.1. Landowner's problem

A representative landowner manages an even-aged stand of trees. The per-unit volume stumpage value is the delivered log price (p) net of harvesting costs (c_h) and the per-unit volume harvest tax (τ). The function $F(T)$ defines the volume of merchantable timber available for harvest at any given age T. The timber yield function takes the standard sigmoid shape.[17] The net revenue from harvest at age T is defined as:

$$R(T) = (p - c_h - \tau)F(T). \qquad (1)$$

The real discount rate is defined as r and the stand establishment cost by c_0.

[17] The yield function is assumed to have the standard sigmoid shape with $F'(T) > 0, F''(T) > 0$ before an inflection point, and $F'(T) > 0, F''(T) < 0$ after an inflection point.

The stand is subject to a wildfire risk. The average annual arrival rate is denoted by λ. Following Reed (1984), the fire arrival is modeled using a homogenous Poisson process. We furthermore assume that the average arrival rate is a strictly decreasing function of the annual level of investment in risk mitigation, $\lambda'(y) < 0$, (Reed, 1989). Mitigation effort, y, is broadly defined as investment into fire preparedness, "initial attack" or "extended attack" wildfire suppression response which serves to reduce fire spread rates. Let the random variable X denote the time between each forest growth cycle, either due to a clearcut harvest or a wildfire disturbance. The probability of a fire disturbance occurring before the harvest age is defined as $\Pr[X < T] = 1 - e^{-T\lambda(y)}$, while the probability of the stand reaching the rotation age before a disturbance occurs is $\Pr[X = T] = e^{-T\lambda(y)}$. To simplify the model, we assume that there is no salvage harvesting.[18]

We follow the approach taken by van Kooten et al. (1995) to define the payments for carbon released and stored during the rotation. Let p_c denote the price of carbon, k be the carbon dioxide sequestered per unit volume of timber, and η represent the portion of the stand's carbon content released during a fire.[19] When a fire occurs before the chosen harvest age, T, the net future revenue is given by:

$$Y_1 = e^{rX} p_c k \int_0^X F'(x) e^{-rx} dx - p_c k \eta F(X) - c_0 e^{rX}. \tag{2}$$

The first term in (2) represents the compounded carbon payments up to age X. The third term, $p_c k \eta F(X)$, represents the cost of carbon released from a fire disturbance. The term $c_0 e^{rX}$ gives

[18] Salvage harvesting can be incorporated as in Reed (1984) by decreasing the cost of a destructive event. Including the possibility of salvage harvesting will not qualitatively change our results.
[19] Below-ground carbon can be retained in soil following a fire disturbance and some above-ground carbon may be retained following a low- to mid-severity fire.

the compounded cost of stand establishment. When the harvest age arrives before a fire destroys the standing timber stock, the net future revenues are given by:

$$Y_2 = R(T) + e^{rT} p_c k \int_0^T F'(t) e^{-rt} dt - p_c k(1-\theta)F(T) - c_0 e^{rT}. \tag{3}$$

At the clearcut age, a fraction θ of the carbon content on the stand is sequestered in long-lived wood products.[20] The rest of the carbon is released at the time of the clearcut.

To summarize the random payoffs, we have:

$$Y = \begin{cases} Y_1 & if\ X < T \\ Y_2 & if\ X = T \end{cases}$$

As shown by Reed (1984), a risk neutral landowner's objective function can be written as:

$$V(T) = \frac{\mathrm{E}[e^{-rX}Y]}{\mathrm{E}[1-e^{-rX}]} - \frac{\omega}{r}. \tag{4}$$

The last term with parameter ω represents the present value of annual per-acre tax expenses. For a given choice of T, Eq. (4) gives the expected value of the bare land conditional on the set of parameters that are exogenous from the perspective of the landowner, $\mathbf{\Omega} = (p, c_h, p_c, y, \tau, \omega, c_0, C, k, \theta, \eta)$. A risk neutral landowner's objective is to maximize the expression in (4) by choosing the optimal rotation age.[21] The first order condition of the objective function (4) defines the optimal rotation age as a function of exogenous parameters $T^*(\mathbf{\Omega})$. The second order condition for the maximum is assumed to hold.

[20] Long-lived wood products are those which do not decay before long-term use in construction, such as framing lumber, plywood, or structural wood panels manufactured from softwood timber.

[21] Using the expressions in (2) and (3) and the Poisson process probabilities, the full expression for the objective function in (4), is derived in Appendix A.

Most of the comparative statics of the optimal solution are in general well known (e.g. Chang, 1982; Amacher et al., 2009). For example, a higher harvest tax will lengthen the rotation $\left(\frac{\partial T^*}{\partial \tau} > 0\right)$ but acre-based site value taxes are neutral, $\left(\frac{\partial T^*}{\partial \omega} = 0\right)$. Higher timber prices will shorten the rotation age $\left(\frac{\partial T^*}{\partial p} < 0\right)$ while higher establishment costs will lengthen it $\left(\frac{\partial T^*}{\partial c_0} > 0\right)$. Risk raises the risk-adjusted discount rate (Reed, 1984; Insley and Lei, 2007), and so lowers the rotation age. Greater investment in fire protection (y) will raise the rotation age $\left(\frac{\partial T^*}{\partial y} > 0\right)$ since by assumption, risk is also reduced (see Reed, 1989). A larger fraction of carbon stored in wood products will shorten the rotation age $\left(\frac{\partial T^*}{\partial \theta} < 0\right)$ (van Kooten et al., 1995). A larger carbon price (p_c) and a larger quantity of carbon sequestered per unit of merchantable volume (k) will raise the landowner's rotation age $\left(\frac{\partial T^*}{\partial p_c} > 0; \frac{\partial T^*}{\partial k} < 0\right)$, whereas a greater percentage of carbon released from a fire will shorten the rotation age $\left(\frac{\partial T^*}{\partial \eta} < 0\right)$.

3.2.2. Planner's problem

The planner uses either a harvest tax or an area-based assessment to fund risk mitigation expenditures (or both). For a given rotation age T, the planner's intertemporal budget constraint can be written as:

$$\frac{\big(r + \lambda(y)\big)e^{-(r+\lambda(y))T}\tau F(T)}{r\big(1 - e^{-(r+\lambda(y))T}\big)} + \frac{\omega}{r} = \frac{y}{r} + G. \qquad (5)$$

The first term on the left-hand side of (5) represents the present value of expected harvest tax receipts (see Appendix B). It is an expected value since the arrival of a fire event during any rotation also means that there are no harvest tax receipts from that rotation. Additionally, it is worth pointing out that larger harvest volumes, and hence longer rotations, translate to greater tax receipts. The second term on the left-hand side is the present value of area-based assessments. The right hand side expresses all expenditures, including the present value of annual per acre risk mitigation expenditures (y/r) plus the present value of all other annual per-acre revenue requirements minus per-acre risk mitigation funding from non-forest tax sources (G).[22] The sum of these expected present value revenues (left-hand side of equation (5)) must equal the present value of annual expenditures (right-hand side of equation (5)).

The planner chooses the values of (ω, τ, y) with knowledge of the landowner's optimal response function $T^*(\boldsymbol{\Omega})$. In other words, the planner acts as a Stackelberg leader. We assume that the planner's objective function is aligned with the landowner's objective but with the addition of the budget constraint. In its general form, the planner's problem can be written as:

$$\max_{\tau\geq 0, \omega \geq 0, y \geq 0} V\big(T^*(\boldsymbol{\Omega})\big) \quad subject\ to\ Eq. (5).$$

Additionally, the expected bare land value must be non-negative. Otherwise, forest ownership would be abandoned.

Given the parameter values, the solutions to the planner's problem provide information on the equilibrium productivity of the stand. One such measure is the expected long run timber supply under stochastic production, as defined by Reed (1984), which is given by:

$$\frac{\mathrm{E}[F]}{\mathrm{E}[X]} = \frac{\lambda F\big(T^*(\boldsymbol{\Omega})\big)}{(1 - e^{-\lambda T^*(\boldsymbol{\Omega})})}. \tag{6}$$

Similarly, we can define the expected long run carbon uptake under stochastic production as

$$\frac{\mathrm{E}[B]}{\mathrm{E}[X]} = \frac{\lambda k \left(F\big(T^*(\boldsymbol{\Omega})\big) + \lambda \int_0^{T^*(\boldsymbol{\Omega})} e^{-\lambda x} dx + F'\big(T^*(\boldsymbol{\Omega})\big) e^{-\lambda T^*(\boldsymbol{\Omega})} \right)}{(1 - e^{-\lambda T^*(\boldsymbol{\Omega})})}.$$

[22] See Appendix C.

(7)

These measures of stand productivity can be solved under different combinations of the exogenous parameters $\mathbf{\Omega}$ to determine the effects of different parameters on timber and carbon productivity.

Characterization of the solution to the planner's problem is analytically difficult and hence we resort to examining numerical solutions. However, it is still worthwhile to examine and compare in detail three potential policy scenarios: one where only acre-based taxes are available to the planner, one where only yield taxes are available to the planner, and the case where both taxes are available.

3.2.2.1. Case1: Acre-based assessment

Suppose that only an area-based assessment is levied and there is no harvest tax ($\omega \geq 0, \tau = 0$). The constraint (5) then defines the area assessment as a function of risk mitigation expenditures:

$$\omega = y + rG.$$

Using this relationship and the landowner's response function T^*, the planner's problem becomes:

$$\max_{y \geq 0} \left\{ \frac{r + \lambda(y)}{r\left(1 - e^{-(r+\lambda(y))T^*}\right)} \left\{ e^{-(r+\lambda(y))T^*}[(p - c_h)F(T^*) + p_c k\theta F(T^*)] - c_0 \right.\right.$$
$$+ rp_c k \left[\lambda(y) \left(\int_0^{T^*} e^{-\lambda(y)x} \left(\int_0^x e^{-rz} F(z) dz \right) dx + \int_0^{T^*} (1 - \eta) e^{-(r+\lambda(y))x} F(x) dx \right) \right.$$
$$\left.\left.\left. + e^{-\lambda(y)T^*} \int_0^{T^*} e^{-rz} F(z) dz \right]\right\} - \frac{y + rG}{r} \right\}. \qquad (8)$$

The planner's solution to problem (8) is the per-acre expenditures on fire risk mitigation: $y^*\big(p_c, T^*(\mathbf{\Omega})\big)$. An application of the implicit function theorem on the solution gives an expression for the total effect of carbon prices on the planner's choice of the acre-based assessment:

$$\frac{d\omega^*}{dp_c} = \frac{\partial \omega^*}{\partial y^*}\left[\left(\frac{\partial y^*}{\partial p_c}\right) + \left(\frac{\partial y^*}{\partial T^*}\right)\left(\frac{\partial T^*}{\partial p_c}\right)\right]. \tag{9}$$

The first term in equation (9) is the direct effect on the planner's tax policy from a change in the carbon price: $\frac{\partial \omega^*}{\partial y^*}\left(\frac{\partial y^*}{\partial p_c}\right)$. The second term in (9) is the indirect effect, arising from the planner's reaction to the landowner's best response to the price change: $\frac{\partial \omega^*}{\partial y^*}\left(\frac{\partial y^*}{\partial T^*}\right)\left(\frac{\partial T^*}{\partial p_c}\right)$. The acre-based assessment required to finance the optimal expenditures defined by the solution to (8) is: $\omega^* = y^*\big(p_c, T^*(\mathbf{\Omega})\big) + rG$. Therefore, $\frac{\partial \omega^*}{\partial y^*} = 1$. However, since we do not know the signs of $\frac{\partial y^*}{\partial p_c}$ or $\frac{\partial y^*}{\partial T^*}$, the sign of equation (9) is ambiguous. For plausible values of the model parameters, we expect to see the landowner's rotation age induce greater mitigation effort $\left(\frac{\partial y^*}{\partial T^*} > 0\right)$, since a longer rotation age enhances the value of land at risk of disturbance. Likewise, we expect $\frac{\partial y^*}{\partial p_c} > 0$, so that the total effect will be positive. A positive relationship $\left(\frac{d\omega^*}{dp_c} > 0\right)$ would suggest that an increase in carbon price would require the planner to raise acre-based assessments in order to finance greater expenditures on fire risk mitigation. Notice that when carbon sequestration benefits are not internalized by the landowner, then the indirect effect is 0.

3.2.2.2. Case 2: Harvest tax

Suppose now that only a harvest tax is levied and there is no area-based assessment ($\omega = 0, \tau \geq 0$). The constraint (5) then implicitly defines the harvest tax as a function of risk mitigation expenditures: $\tau^* = \tau\left(y^*\left(p_c, T^*(\boldsymbol{\Omega})\right)\right)$. Using this constraint, equations (4) and (7), and the landowner's response function $T^*(\boldsymbol{\Omega})$, the planner's problem becomes:

$$\max_{y\geq 0}\left\{\frac{r+\lambda(y)}{r\left(1-e^{-(r+\lambda(y))T^*}\right)}\left\{e^{-(r+\lambda(y))T^*}[(p-\tau(y)-c_h)F(T^*)+p_c k\theta F(T^*)]-c_0\right.\right.$$
$$+rp_c k\left[\lambda(y)\left(\int_0^{T^*} e^{-\lambda(y)x}\left(\int_0^{x} e^{-rz}F(z)dz\right)dx+\int_0^{T^*}(1-\eta)e^{-(r+\lambda(y))x}F(x)dx\right)\right.$$
$$\left.\left.\left.+e^{-\lambda(y)T^*}\int_0^{T^*} e^{-rz}F(z)dz\right]\right\}\right\}. \qquad (10)$$

Again, the planner's policy rule is written as $y^*\left(p_c, T^*(\boldsymbol{\Omega})\right)$ and we seek to investigate the effects of carbon price on this policy. An application of the implicit function theorem on the solution gives an expression for the total effect of carbon prices on the planner's choice of the acre-based assessment:

$$\frac{d\tau^*}{dp_c} = \frac{\partial\tau^*}{\partial y^*}\left[\left(\frac{\partial y^*}{\partial p_c}\right)+\left(\frac{\partial y^*}{\partial T^*}\right)\left(\frac{\partial T^*}{\partial p_c}\right)\right]. \qquad (11)$$

The direct effect $\frac{\partial\tau^*}{\partial y^*}\left(\frac{\partial y^*}{\partial p_c}\right)$ may be positive or negative, particularly since τ may be increasing or decreasing over different domains of y (see Appendix B). The sign of the indirect effect is then also ambiguous: $\frac{\partial\tau^*}{\partial y^*}\left(\frac{\partial y^*}{\partial T^*}\right)\left(\frac{\partial T^*}{\partial p_c}\right) \lesseqgtr 0$. This tells us that the planner's choice of the harvest tax may be larger or smaller with an increase in carbon prices. Hence if carbon prices increase annual expenditures, then the planner may increase or decrease harvest tax rates $\left(\frac{d\tau^*}{dp_c} \gtreqless 0\right)$. Again, note that when carbon sequestration benefits are not internalized by the landowner, then the indirect effect is 0.

3.2.2.3. Case 3: Both tax instruments

With both tax instruments available ($\omega \geq 0, \tau \geq 0$), the planner's problem can be solved using constrained optimization. The Lagrangian function for this problem is:

$$L(y,\omega,\tau,\Lambda) = \frac{r+\lambda(y)}{r\left(1-e^{-(r+\lambda(y))T^*}\right)}\Bigg\{e^{-(r+\lambda(y))T^*}[(p-\tau-c_h)F(T^*)+p_c k\theta F(T^*)]-c_0$$
$$+rp_c k\left[\lambda(y)\left(\int_0^{T^*} e^{-\lambda(y)x}\left(\int_0^x e^{-rz}F(z)dz\right)dx+\int_0^{T^*}(1-\eta)e^{-(r+\lambda(y))x}F(x)dx\right)\right.$$
$$\left.+e^{-\lambda(y)T^*}\int_0^{T^*} e^{-rz}F(z)dz\right]\Bigg\}-\frac{\omega}{r}-\Lambda\left[G+\frac{y-\omega}{r}-\tau\left(\frac{\left(r+\lambda(y)\right)e^{-(r+\lambda(y))}F(T^*)}{r\left(1-e^{-(r+\lambda(y))T^*}\right)}\right)\right] \quad (12)$$

With the following first-order conditions:

$$\frac{\partial L}{\partial y^*} = \frac{\partial L}{\partial \omega^*} = \frac{\partial L}{\partial \tau^*} = \frac{\partial L}{\partial \Lambda^*} = 0. \quad (13)$$

In equation (12), variable Λ is the Lagrange multiplier associated with the constraint from equation (7). At the solution, Λ^* gives the shadow price of an increase in tax revenues. Note that $\Lambda^* = 1$ since the neutral area-based tax is available (Koskela and Ollikainen, 2003).[23] The planner's solution is a time-invariant commitment to a tax and spending program: (y^*, ω^*, τ^*).

3.3. Numerical Analysis

This section outlines the chosen parameters, functional forms, and the computational approach used to solve a specific case of the two-stage model. We focus on parameters specific to the management of forestlands in Oregon's western Cascade region. All parameters and functional forms used in the numerical exercise are displayed in Table 3.1.

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[23] Additionally, non-negativity constraints should be included in the Lagrangian equation (10), but they have been excluded here to simplify the notation.

Table 3.1 - Parameters and Functional Forms used for Numerical Analysis

	Exogenous Parameters	
k	Tons of CO2 sequestered per MBF of timber volume	10.53
η	Fraction of stand's carbon pool released during fire	$\eta \in \{0.22,1.00\}$
θ	Fraction of carbon stored long-term in wood products	$\theta \in \{0.02,0.42\}$
a	First parameter of the timber yield equation	101.4019
b	Second parameter of the timber yield equation	0.0247
c	Third parameter of the timber yield equation	3.0
β	Factor productivity of fire suppression	0.005
ρ	Output elasticity of fire suppression	0.21
p	Douglas-fir sawlog delivered price ($/MBF)	796
c_h	Cost of clearcut harvest, including hauling ($/MBF)	400
c_0	Stand establishment costs ($/ac.)	210
r	Real discount rate	0.04
G	Planner's budget constraint ($)	$-0.17/r$
p_c	Carbon credit price ($/ton)	[0,30]
	Planner's Policy Instruments	**Domain**
y	Annual expenditures on fire suppression ($/ac./year)	$[0,\infty)$
τ	Unit tax on harvest ($/MBF)	$[0,\infty)$
ω	Area-based tax used to fund fire suppression ($/ac./year)	$[0,\infty)$
	Landowner's Decision Variable	**Domain**
T	Harvest rotation age or "period of production" (years)	$[0,\infty)$
	Technological Relationships	**Range**
$F(T) = a\left(1 - e^{-bT}\right)^c$	Timber yield (MBF/ac.)	$[0,\infty)$
$B(T) = k\int_0^T F'(t)dt.$	Carbon Sequestration (tons CO2/ac.)	$[0,\infty)$
$\lambda(y) = \beta y^{-\rho}$	Wildfire Arrival Rate	[0.001,0.03]

3.3.1. Economic parameters

We use price and cost information for delivered Douglas-fir logs, logging and hauling costs, and stand establishment costs reported by Diaz et al. (2018). The delivered log price is $796/MBF, the cost of harvesting and transportation $400/MBF, and the establishment cost is $200/acre. To represent the value of a ton of carbon, we choose a range of values that are aligned with the recent carbon offset credit prices sold in the California-Quebec joint auction. These values range from \$10 to \$20 per ton of CO2 equivalent.[24] We set the annual real discount rate to equal 4 percent.

In Oregon, a Forest Products Harvest Tax or “FPHT” (ORS 321.005-321.152) is levied as a unit tax on timber harvests and has been recently set at a rate of \$4.13 per thousand board feet (MBF).[25] Around 18 percent of the FPHT receipts are used to finance wildfire risk reduction programs in the state through the Oregon Forestland Protection Fund (OFLPF)[26]. The other 82 percent of FPHT receipts are used to fund research, forestry education, and the administration of the Oregon Forest Practices Act. Approximately \$12 million is raised annually from the FPHT (ODF, 2013), so an annual average of \$9.84 million is raised from harvest taxes to fund non-fire suppression related public works. Area-based land taxes called “Fire Patrol Assessments” (ORS 477.880 and ORS 477.295) are also used to fund initial attack fire suppression efforts and the OFLPF. The Fire Patrol Assessments are to be assessed as the maximum of either \$0.6565 per acre of a taxable lot per year (Elwood et al., 2006) or a fixed amount of \$18.75 per year for taxable lots smaller than 28.65 acres (Cook and Becker, 2017; Elwood et al., 2006). However, this rate depends on the fire protection district in which the forest parcel is assessed (Cook and Becker, 2017).[27] Of these tax assessments, 100 percent of the tax receipts from Fire Patrol Assessments are allocated towards fire protection and suppression services. Additionally, an average of \$3.61 per acre in property taxes are levied on forestlands in western Oregon (Elwood et al., 2006). Including the Forest Patrol Assessments, this gives an expected annual per-acre land tax rate of \$4.31.

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[24] https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program

[25] https://www.oregon.gov/DOR/programs/property/Pages/timber-rates-current.aspx

[26] https://www.oregon.gov/dor/programs/property/Pages/timber-tax.aspx

[27] An additional \$0.05 per acre is charged for fire suppression services in Western Oregon (Cook and Becker, 2017).

All other suppression expenditures on 16 million acres[28] protected by the state of Oregon are funded from three other sources besides forest-based taxes: 1) the state's General Fund, 2) a suppression cost insurance policy, and 3) federal grants from the Federal Emergency Management Agency (FEMA). From 2006 to 2015, Oregon's General Tax Fund after insurance claims has covered an annual average of $4.28 million of state suppression expenditures (this excludes contributions from "base layer" funding from Forest Patrol Assessments and Forest Urban Interface Lands Assessments). Insurance claims collected through the state's suppression cost insurance policy with Lloyd's of London have covered an average of $5.0 million annually while premiums have averaged $1.35 million annually (Cook and Becker, 2017). Grants to suppress fires from FEMA have averaged $8.4 million annually over this same period (Cook and Becker, 2017). In total, fire suppression costs funded through non-forest tax sources (including insurance premiums) have been an average of $0.79 per acre per year. Given that $0.62 per acre per year is raised from harvest taxes to fund non-suppression related public works, the revenues raised from harvest taxes are less than suppression expenditures from non-forest tax sources, so we use a revenue requirement of -$0.17 per acre (the present value of this annual cost at a discount rate of 4 percent is: $G = -4.3$).

3.3.2. Ecological parameters

A sigmoid-shaped "von Bertalanfy" yield function $F(T)$ is used to express the volume of merchantable Douglas-fir timber on per acre on a high-quality site in Western Oregon (Hashida and Lewis, 2019; Hudiburg et al., 2009). Coefficients provided by Hashida and Lewis (2019) provide the growth and yield parameters for a representative stand presented in Table 1. With these

[28] https://www.oregon.gov/ODF/Documents/AboutODF/ODFAgencyBrochure.pdf

parameters (a, b, c), the rotation age which maximizes volume (i.e. the "biological rotation age") occurs at age 77, where the mean annual increment (MAI) and the current annual increments (CAI) are equivalent. Following van Kooten et al. (1995), the total carbon sequestered by the forest from its establishment up to age T (given in tons per acre) is given by a scaled integration of the CAI curve (see Table 1). This form of the sequestration function allows carbon sequestration revenues to accumulate on the stand at a decreasing rate.

The arrival rate of a stand-replacing fire on the Douglas-fir dominated forests of the Western Cascades region is one in every 200+ years ($\lambda < 0.005$), while low- to mixed-severity fire occurs between once in every 35 years ($\lambda = 0.0286$) and once in every 200 years ($\lambda = 0.005$), (Wolf et al., 2015). This maximum fire return interval for a stand-replacing fire gives an upper bound which we can use for the factor productivity of suppression ($\beta = 0.005$).

Approximately 223 tons of carbon per acre are stored by age 100 in the Western Cascades region under minimal disturbance conditions (Hudiburg et al., 2009). Given the yield parameters (a, b, c), suggesting that about 2.87 tons of carbon are stored per unit of timber volume at age 100, requiring a parameter of $k = 10.53$ in the carbon benefits function.[29] We assume that between 2 percent (Harmon et al, 1996) and 42.1 percent (Diaz et al., 2018) of standing carbon is stored long-term in manufactured wood products. We also assume that 100 percent of stand-level carbon pools are released from fire under a "full destruction" scenario. However, we also test partial destruction by assuming that 22 percent of stand-level carbon pools are released from fire (based on expectations from mixed-severity fire data; see Law and Waring, 2015).

[29] Since carbon is priced in terms of its carbon dioxide equivalent mass (CARB, 2012), we set $k = 2.87 * 3.67$ in the amenity benefits function, where 3.67 represents the mass of carbon dioxide equivalent per ton of carbon.

3.3.3. Model Calibration

To investigate the impact of wildfire suppression effectiveness, a relatively flexible production relationship is specified for the fire arrival rate (see Table 1). The parameter ρ is the output elasticity of suppression. Every percentage increase in suppression expenditures will reduce the arrival rate by ρ percent. As this effectiveness of suppression expenditures increases, the parameter ρ increases and the fire arrival rate falls at a faster rate for any incremental increase in suppression. If $\rho < 1$, the suppression technology displays decreasing returns to scale. If $\rho > 1$, the suppression technology displays increasing returns to scale. Note that this specification of the arrival function assumes that fire occurrence is independent of the age of the forest. This derives from the assumption of a homogeneous Poisson process for the fire arrival, which means that fire arrival risk does not increase or decrease as the stand matures.

Given current tax rates, the revenue constraint, and typical rotation lengths for working timberlands in the study region (T^o), we calibrate the first stage model (case 1) to solve for the unknown value of the output elasticity. This calibration is conducted for two alternative climate scenarios: 1) a frequent, low-severity fire regime ($\beta = 0.0286, \eta = 0.22$), and 2) a low-frequency, high-severity fire regime ($\beta = 0.005, \eta = 1.0$).This entails a root-finding problem to equate the planner's solution with observed site values (assuming no participation in carbon offset markets):

$$0 = V_s(T^o; \beta, \eta) - V_s\big(T(y^*(\rho; \beta, \eta))\big) \tag{12}$$

Under the frequent, low-severity regime, if we assume that the arrival rate of high severity fire is one event every 200 years ($\lambda = 0.005$) and the typical rotation age of plantation forests managed solely for timber in this region is between 35 and 40 years, we solve for an implied elasticity of $\rho = 0.61$ if $T = 35$ and $\rho = 0.48$ if $T = 40$. If instead we assume that a high severity event occurs more frequently at a rate of once in every 100 years ($\lambda = 0.01$), the implied output elasticity for these rotation lengths is $\rho = 0.18$ if $T = 35$ and $\rho = 0.14$ if $T = 40$. The calibration exercise shows that assuming a more frequent fire regime (i.e. a larger λ), would imply less effectiveness of suppression investment under current management conditions.

Under the less-frequent, high-severity fire regime, if we assume that the arrival rate of high severity fire is one event every 333.3 years ($\lambda = 0.0030$) and the typical rotation age of planation forests managed solely for timber in this region is between 35 and 40 years, we solve for an implied elasticity of $\rho = 0.31$ if $T = 35$ and $\rho = 0.27$ if $T = 40$. If instead we assume that a high severity event occurs more frequently at a rate of once in every 250 years ($\lambda = 0.0040$), the implied output elasticity for these rotation lengths is $\rho = 0.14$ if $T = 35$ and $\rho = 0.11$ if $T = 40$.

3.3.4. Computational methods

An exact numerical form of the landowner's problem and the planner's problem with a single tax instrument (cases 1 and 2) can be solved using standard unconstrained nonlinear programming techniques in MATLAB, such as a Nelder-Mead (NM) algorithm (Miranda and Fackler, 2002). The NM algorithm is a derivative free method, and so iterations of the algorithm only require a specification of the objective function to be maximized. Each iteration of the NM algorithm gives a candidate solution $\tilde{T}^*$, which requires a numerical integration of the carbon benefits function in order to approximate the expected net revenues until the algorithm converges on the final solution T^*. For each iteration, a Newton-Cotes quadrature approximation of the carbon benefits function is calculated using routines from the "COMPECON" toolbox (Miranda and Fackler, 2002). This computation enables a new evaluation of the objective function for each combination of p_c and λ on the interval $[0,50] \times [0.001,0.03]$. A check for proper convergence of the algorithm is conducted for each combination of p_c and λ to ensure the existence of a maximum solution.

The planner's first-stage solution with both tax instruments (case 3) is a constrained optimization problem and so can be solved using a sequential quadratic programming (SQP) algorithm (Venkataraman, 2009). The landowner's best response function defines the relationship between T^* and the planner's tax policy, therefore the budget constraint is a nonlinear function of τ, ω, and y. Each iteration of the SQP algorithm entails an approximation of the best response function, which can be obtained using the NM algorithm. Similarly, the harvest tax rate implied by equation (5) requires an additional fixed-point iteration using the approximated Best Response function. A bisection algorithm (Miranda and Fackler, 2002) is used to approximate this tax rate for each iteration of the SQP algorithm. A numerical check of the second-order conditions is conducted after each solution found using the SQP algorithm under exogenous combinations of p_c and $T^*(p_c, \lambda)$. The resulting data under both the single tax and mixed-tax scenarios is plotted in the following section to understand the sensitivity of the sequential equilibrium solution to changes in the various components of the planners' tax and suppression expenditure policy.

Solutions to the landowner's problem can be verified by checking the result against solutions from standard benchmark land value models. For example, setting $\lambda = 0,$ and $p_c = 0$ will yield the standard Faustmann solution, which would occur if no carbon markets or disturbance risk were present. Setting $\lambda = 0$ but allowing $p_c > 0$ will yield the solution presented by van Kooten et al. (1995). Setting $\lambda > 0$ but $p_c = 0$ will yield the Reed (1984) solution. Finally, setting both $\lambda > 0$ and $p_c > 0$ will yield a solution identical to the one reported by Englin et al. (2000) or Ekholm (2020). Solutions to the planner's problem (case 3) can be verified by setting $G = 0, p_c = 0,$ and $\lambda = 0$, to yield a case where no tax is first-best optimal in a deterministic setting with no external environmental amenity values ($y^* = 0, \tau^* = 0, \omega^* = 0$), as shown by Hellsten (1988). Setting $G > 0, p_c = 0$, and $\lambda = 0$ in the planner's problem (case 3) yields a solution where only a neutral tax is second-best optimal for meeting the revenue target in the deterministic setting with no amenities ($y^* = 0, \tau^* = 0, \omega^* > 0$), as reported by Koskela and Ollikainen (2003). Solutions to the planner's problem in a deterministic setting (case 3) can be further verified by setting allowing carbon sequestration to be a pure public good and by setting $G = 0, p_c > 0$, and $\lambda = 0$ to show that a distortionary (Pigouvian) tax instrument is optimal when environmental amenities are not internalized by the landowner ($y^* = 0, \tau^* > 0, \omega^* = 0$), as also reported by Koskela and Ollikainen (2003).

3.4. Results

Solutions to the model and the three different cases are called Stackelberg equilibrium solutions. These policy outcomes are subgame perfect equilibria. Alternative taxation schemes will shift the expected marginal value of delaying harvest, and so will have differing impacts on both timber and carbon productivity. We examine these effects in Table 3.2, which shows the Stackelberg equilibrium when both taxes are available to the planner (Case 3) under the baseline set of parameters ($\theta = 0.42, \eta = 1.0, \beta = 0.005$) and when the full benefits of carbon sequestration are either internalized or not internalized by the landowner. We see in Table 3.2 that when carbon benefits are internalized, a higher carbon price raises the optimal tax rates and the associated annual suppression expenditures per acre. This suggests that either the indirect effects in equations (9) and (11) are positive, or that the positive direct effects of a higher carbon price dominate any potentially negative indirect effects from a higher carbon price. As a point of comparison, the Faustmann solution (no risk, no carbon benefits) is 36.4 years for the baseline set of parameters given in Table 3.1.

Table 3.2 - Solutions to Case 3 under Endogenous Fire Risk (with and without carbon payments)

Carbon Value	Acre-based tax ($\boldsymbol{\omega}^*$)	Unit tax ($\boldsymbol{\tau}^*$)	Suppression Expenditures ($\boldsymbol{y}^*$)	Arrival rate ($\boldsymbol{\lambda}^*$)	Rotation age ($\boldsymbol{T}^*$)	Social bare land value ($\boldsymbol{V}_{\boldsymbol{S}}^*$)	Landowner's bare land value ($\boldsymbol{V}^*$)
$\boldsymbol{p_c} = \$\mathbf{0}$/ton (no value of carbon storage)	\$1.8/ac./yr.	\$0.0/MBF	\$1.2/ac./yr.	0.0043	34.5 yrs.	\$1,980/ac.	\$1,980/ac.
$\boldsymbol{p_c} = \$\mathbf{20}$/ton (not internalized)	\$0.0/ac./yr.	\$12.3/MBF	\$2.3/ac./yr.	0.0040	34.7 yrs.	\$3,319/ac.	\$1,973/ac.
$\boldsymbol{p_c} = \$\mathbf{20}$/ton (internalized)	\$3.1/ac./yr.	\$0.0/MBF	\$2.5/ac./yr.	0.0039	45.2 yrs.	\$3,499/ac.	\$3,499/ac.
$\boldsymbol{p_c} = \$\mathbf{30}$/ton (not internalized)	\$0.0/ac./yr.	\$14.5/MBF	\$2.8/ac./yr.	0.0038	34.8 yrs.	\$3,993/ac.	\$1,967/ac.
$\boldsymbol{p_c} = \$\mathbf{30}$/ton (internalized)	\$3.9/ac./yr.	\$0.0/MBF	\$3.3/ac./yr.	0.0037	51.5 yrs.	\$4,397/ac.	\$4,397/ac.
$\boldsymbol{p_c} = \$\mathbf{50}$/ton (not internalized)	\$0.0/ac./yr.	\$18.9/MBF	\$3.9/ac./yr.	0.0036	34.9 yrs.	\$5,348/ac.	\$1,951/ac.
$\boldsymbol{p_c} = \$\mathbf{50}$/ton (internalized)	\$5.8/ac./yr.	\$0.0/MBF	\$5.2/ac./yr.	0.0034	67.5 yrs.	\$6,449/ac.	\$6,449/ac.

We also see from Table 3.2, that when there is no social value from forest carbon storage, the private and social land values are the same (\$1,980/ac.) and the stand is rotated every 34.5 years. When sequestration has value to society but its benefits are not accounted for by the landowner, the harvest tax acts as a Pigouvian instrument and generates a larger land value from society's perspective than what can be achieved with an acre-based land tax or a mix of both harvest taxes and the acre-based land tax. At a carbon price of \$20/ton, the planner sets a harvest tax rate equal to \$12.3/MBF, which enables annual suppression expenditures of \$2.3 per acre and an arrival rate of one event every 250 years ($\lambda^* = 0.0040$). This policy generates a response from the landowner to harvest once every 34.7 years and a land value of $1,973 per acre.

However, with the harvest tax policy, the equilibrium rotation age is no longer able to accommodate society's value for carbon stored in forests, so the social value of the bare land is larger than the private value by $1,346 per acre. This result reflects the ineffectiveness of harvest taxes when used as a Pigouvian instrument. A harvest tax increase from $5/MBF to $15/MBF reflects only a $10 reduction in net stumpage value. We see in Table 3.2 that a higher carbon price will raise the planner's choice of the harvest tax rate, increase annual per acre suppression expenditures, and lengthen the landowner's rotation age, albeit by only a small margin since the landowner does not consider the value of carbon in their rotation decision and the planner's budget constraint is binding. The distortionary effect from the harvest tax is not large enough to offset the reduction in the rotation age from the landowner's inability to account for the benefits of carbon sequestration. Given a higher carbon price, the harvest tax policy will also increase the difference between private and social bare land values as the larger harvest tax lowers the net stumpage price.

In the case where carbon *is* internalized by the landowner, the planner's solution maximizes the land value when area-based land taxes are positive, but harvest taxes are set to zero (see Table 3.2). Under any given carbon price, the social bare land value is larger when carbon is internalized, reflecting society's loss from not having an effective Pigouvian instrument available to incentivize the socially optimal delay of the harvest age. In other words, the landowner's private management of carbon sequestration yields a longer rotation age (and higher land value) than what the planner can achieve with a distortionary tax if the landowner does not manage for carbon. This loss from society's perspective, in the case where carbon sequestration benefits are not privately internalized, is larger under a higher carbon price; there is a \$180 difference in V_s^* when $p_c = \$20$/ton and a \$1101 difference in V_s^* when $p_c = \$50$/ton. In Table 2, we see that the private and social value of bare land coincide when the external benefits of carbon sequestration are accounted for by the landowner. For a carbon price of \$20/ton, the annual assessment is \$3.1 per acre. This enables annual suppression expenditures of \$2.5 per acre, which will yield an arrival rate of one event every 256 years ($\lambda^* = 0.0039$), a rotation length of 45.2 years, and a site value of \$3,499 per acre. Also notice that a larger internalized value of carbon sequestration increases the stand's rotation age. An increase in the carbon price from \$20/ton to \$30/ton will lengthen the landowner's rotation age from 45.2 years to 51.5 years. An increase from \$30/ton to \$50/ton will lengthen the landowner's rotation age from 51.5 years to 67.5 years.

The above results (Case 3) carry over to the scenarios where only one of the two tax instruments are available (Cases 1 and 2) since in those scenarios the planner's policy exhibits corner solutions. Whether the planner uses an acre-based tax or a harvest tax depends on the landowner's capacity to internalize the social value of carbon sequestration. When the landowner does not consider the social value of carbon sequestration, Case 3 is identical to the single tax solution of Case 2 (i.e. harvest tax only). When the landowner does consider the social value of sequestration (for example, via participation in an offset market), then Case 3 is identical to the single-tax solution of Case 1 (i.e. acre-based land tax only).

3.4.1. Equilibrium timber and carbon productivity

To compare the impacts of the planner's tax and expenditure policy on equilibrium forest productivity, we show how expected long run timber supply (equation (6)) and expected long run carbon uptake (equation (7)) may change under different carbon prices when carbon benefits are not internalized (Figure 3.1), and when they are (Figure 3.2). These result shows that harvest taxes impact the rotation age through two separate channels, generating a larger overall impact on the stand's timber productivity when carbon benefits are internalized. First, there is a distortionary effect of higher harvest tax rates via a reduction in the fire arrival rate. Second, there is an additional distortionary effect of a harvest tax through its reduction in net stumpage value, which further lengthens the rotation age and increases the expected long run average timber supply and carbon uptake.

Figure 3.1 compares the expected long run timber supply and the expected long run carbon uptake of the forest growing stock under the two single tax solutions (Cases 1 and 2). Under Cases 1 and 2, the expected long run timber supply is lower under the planner's tax policy when carbon prices are higher. Under case 2, timber supply can increase under carbon prices higher than $43/ton (Figure 3.1, left). However, these changes in timber supply are small since the carbon price is not accounted for by the landowner and the harvest tax is ineffective at creating the desired Pigouvian response. There is also a monotonically decreasing relationship between expected long run timber supply and the carbon price under for Case 1 because the per-acre land tax is neutral from the perspective of the landowner. Therefore, when carbon prices are higher, expected timber yield (equation (6)) increases at a slower rate than the expected time between disturbances. Figure 3.1 (right) shows the long run equilibrium carbon productivity of the forest stand under various carbon prices. For both Cases 1 and 2, a higher carbon price increases the planner's optimal tax rate, thereby raising suppression expenditures and lengthening the rotation age such that the expected carbon uptake (equation (7)) increases at a slower rate than the expected time between disturbances.

However, we again note only a small change in the expected long run carbon uptake when the social benefits of sequestration are not internalized. This is because reductions in the arrival rate via investment in risk reduction are not effective Pigouvian instruments since a removal of all risk would limit the rotation length to the Faustmann solution (no risk, no carbon), leaving the full social benefits of carbon still unaccounted for by the landowner. The reason for this low sensitivity of the rotation age to change sin the harvest tax rate is due to the simultaneous effect of the stumpage price (net of the harvest tax) on both the expected marginal benefit of delaying harvest and the expected marginal cost of delaying harvest. When harvest taxes increase, the expected marginal benefit of delaying harvest falls as future harvest revenues become less attractive, but the expected marginal cost of delaying harvest also falls since the landowner can harvest cannot re-invest as much in immediate harvest revenues at the risk-free rate of return. The net effect of a larger harvest tax is a slightly longer rotation age and is identical to the price effect which has been well established as smaller in magnitude than the real interest rate effect (see Samuelson, 1976 or Amacher et al., 2009).

Figure 3.1 - Equilibrium Long-run Productivity with External Benefits of Carbon Sequestration

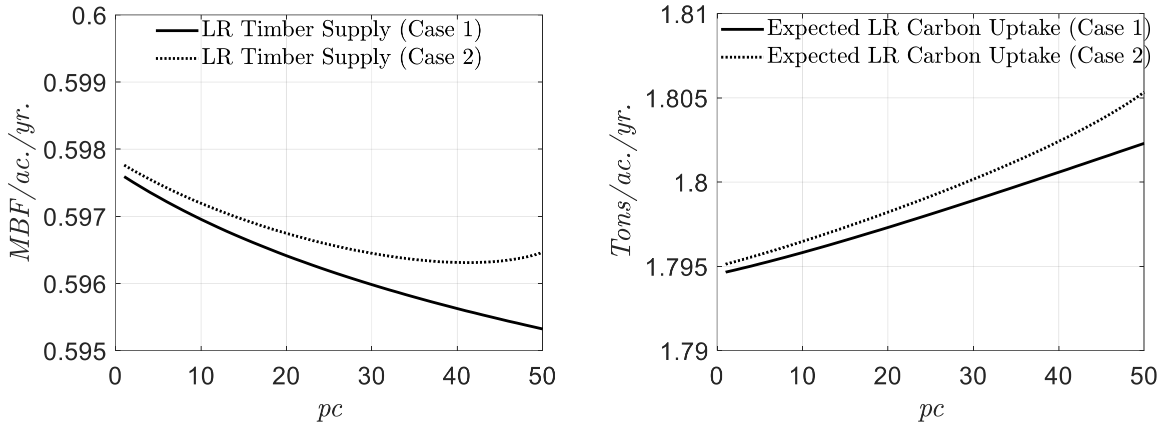

Figure caption: Expected long run (LR) timber supply (left) and expected long run carbon uptake (right) increase when taxes are raised to fund reductions in the fire arrival rate. The stand productivity is larger when a harvest tax is used in lieu of a per-acre assessment.

The solutions are also plotted in Figure 3.2 for different carbon prices when the social value of carbon sequestration *is* internalized by the landowner. We see in Figure 3.2 that long run equilibrium productivity is much more responsive to the carbon price when sequestration benefits are accounted for by the landowner. When carbon prices are low, the average stand productivity (equations (6) and (7)) is larger under the planner's tax policy relative to the no-tax scenario (red curve) with a fixed arrival rate of one event every 200 years. However, the long run timber supply (equation (6)) is larger under a no-tax scenario at higher carbon prices since higher carbon prices and lower risk both work to prolong the time between harvests. We also see that expected annual timber productivity (Figure 3.2, left) and carbon productivity (Figure 3.2, right) are greater with a harvest tax (Case 2) relative to the per-acre land tax (Case 1) across all carbon prices. In both cases, a higher carbon price raises the optimal tax rate and the associated annual suppression expenditures per acre, leading to greater average annual productivity. This again suggests that the positive direct effects in equations (9) and (11) dominate any potentially negative indirect effects.

Figure 3.2 - Equilibrium Long-run Productivity with Internalized Benefits of Carbon Sequestration

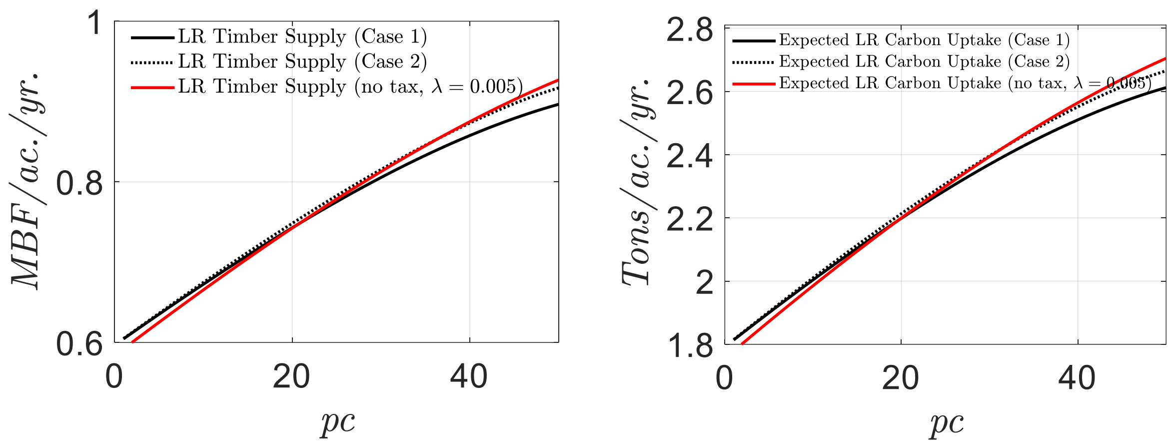

Figure caption: Expected long run (LR) timber supply (left) and expected long run carbon uptake (right) increase when taxes are raised to fund reductions in the fire arrival rate. The stand productivity is larger when a harvest tax is used in lieu of a per-acre assessment.

3.4.2. Endogenous vs. exogenous risk with a carbon externality

When taxes are raised for the purpose of funding reductions in wildfire risk, then risk is endogenously determined in the planner's problem. This determination of risk in the second stage model naturally has an impact on the Stackelberg equilibrium rotation length. It is useful to compare the model solutions from such an endogenous risk case to the case where risk is exogenous from the planner's perspective (i.e. risk level is not responsive to suppression expenditures). Like discussed above, when both tax instruments are available to the planner and the socially optimal level of carbon sequestration *is not* internalized by the landowner, the optimal policy instead consists of a harvest tax only ($\omega^* = 0, \tau^* > 0$). In Figure 3.3, where the landowner does not consider the social value of carbon sequestration and risk is exogenously determined by a fixed level of suppression expenditures ($\lambda(g_o = 0.79)$), increases in the carbon price will not affect the rotation length (dashed line). However, when risk is endogenously determined by harvest tax receipts $(\lambda(y^* + g_o))$, the optimal tax rate increases with higher carbon prices, so the resulting reduction in the fire arrival rate lengthens the rotation age. The increase in the rotation age from the planner's management of risk is small since the higher carbon price does not have any influence in the second stage problem. Additionally, the effect of harvest taxes on rotation age is small, especially when the log price is relatively large.

Figure 3.3 - Rotation Length under Exogenous and Endogenous Risk (Carbon Sequestration Benefits Not Internalized, ω*=0,τ*>0)

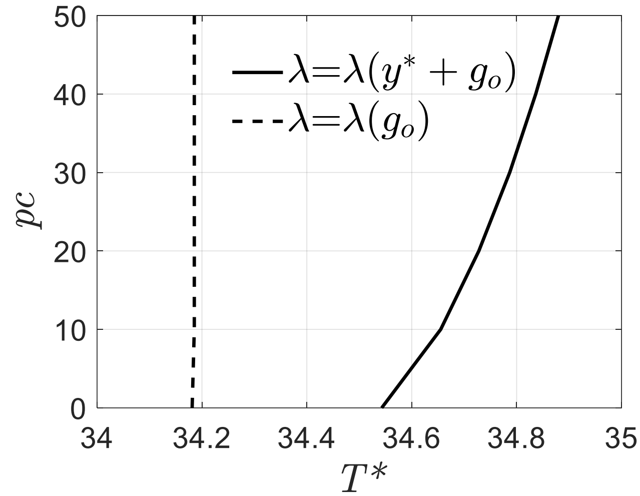

Figure caption: Responsiveness of the Stackelberg equilibrium rotation age (T^*) to higher carbon prices (p_c) under the suppression level attainable without forest taxation (g_o, dashed line) and the suppression level attainable with forest taxation ($y^* + g_o$, solid line).

3.4.3. Endogenous vs. exogenous risk with internalized value of carbon sequestration

When both tax instruments are available to the planner and the socially optimal level of carbon sequestration *is* internalized by the landowner (Case 3), the optimal policy consists of a single tax instrument ($\omega^* > 0, \tau^* = 0$). Notice that, in Figure 3.4, when fire risk is exogenous (dashed line) and annual per-acre suppression expenditures are fixed at a level obtained without forest taxation, ($g_o = 0.79$), the per-acre land tax remains neutral and the only source of an increasing rotation length is a higher carbon price. However, when fire risk reduction is endogenous and afforded by acre-based land tax receipts (solid line), arrival risk falls such that the landowner will further increase their rotation length. When fire risk is endogenous, the Stackelberg equilibrium solution is more responsive to increases in the carbon price than in the case where the risk is exogenous.

Figure 3.4 - Rotation Length under Exogenous and Endogenous Risk (Carbon Sequestration Amenities Internalized, ω*>0,τ*=0)

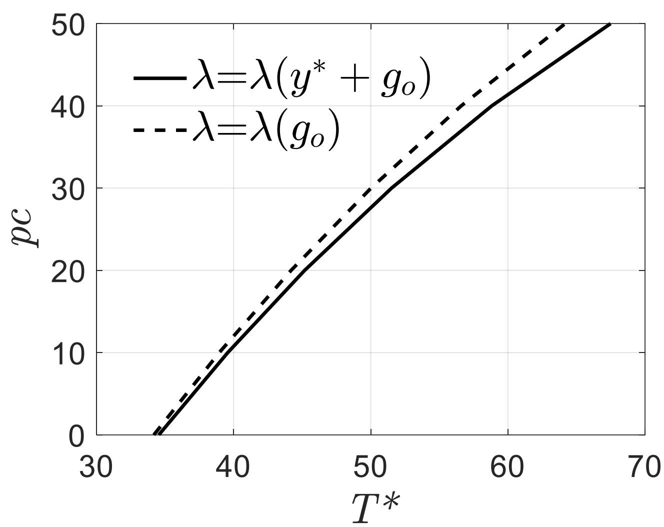

Figure caption: Responsiveness of the Stackelberg equilibrium rotation age (T^*) to higher carbon prices (p_c) under the suppression level attainable without forest taxation (g_o, dashed line) and the suppression level attainable with forest taxation ($y^* + g_o$, solid line).

3.4.4. Sensitivity to carbon storage parameters under endogenous risk

We examine the sensitivity of the above results with respect to two model parameters of interest: 1) the portion of the stand's carbon released after a fire (η), and 2) the share of carbon stored in long-lived wood products (θ). These parameters are controversial and difficult to estimate; so, their sensitivity on equilibrium forest management outcomes is of interest. We focus on a range of values in Figure 4 that have been suggested by others (Diaz et al., 2018; Law and Waring, 2015; Harmon et al., 1996) and that is consistent with a shift in carbon prices from \$1.0 per ton to \$30.0 per ton. In Figure 3.5 (left), the social value of carbon is internalized so we see the subgame-perfect equilibrium effect of endogenous risk and a larger acre-based land tax on the landowner's rotation age. Higher carbon prices require a larger acre-based land tax to afford further reduction in the landowner's fire risk. Higher carbon prices will therefore raise the equilibrium rotation age.

When the social benefits of carbon sequestration are not internalized by the private landowner (as in Figure 3.5, right), the planner's harvest tax policy has a positive impact on the landowner's rotation length, but the effect is not as large since carbon prices do not matter from the landowner's perspective. Since the carbon storage parameters impact the net current value of sequestration, and prices have a limited impact on rotation length when carbon benefits are not privately internalized (see Table 3.2), the shifts in Figure 3.5 (right) are negligible. In both cases (Figure 3.5 left and right) we see that a larger proportion of carbon retained $(1-\eta)$ following a fire will increase the rotation age (as it lowers the cost of a disturbance event). However, the solution is relatively more sensitive to changes in the percentage of carbon stored long-term in wood products (θ), since long-term storage has a positive impact on the benefit of harvest. Note that whether or not carbon storage is internalized by the landowner, the equilibrium rotation age is shorter when more carbon is stored long-term in wood products. This is because greater long-term storage decreases the cost of harvesting, so that there is a larger net current value of timber harvest Y_2. It is well known that a lower harvest cost will shorten the optimal time between harvests since its effect is comparable to that of a higher stumpage price (Amacher et al., 2009, Ch. 2).

Figure 3.5 - Distortionary Effect of Forest Taxes under Endogenous Risk

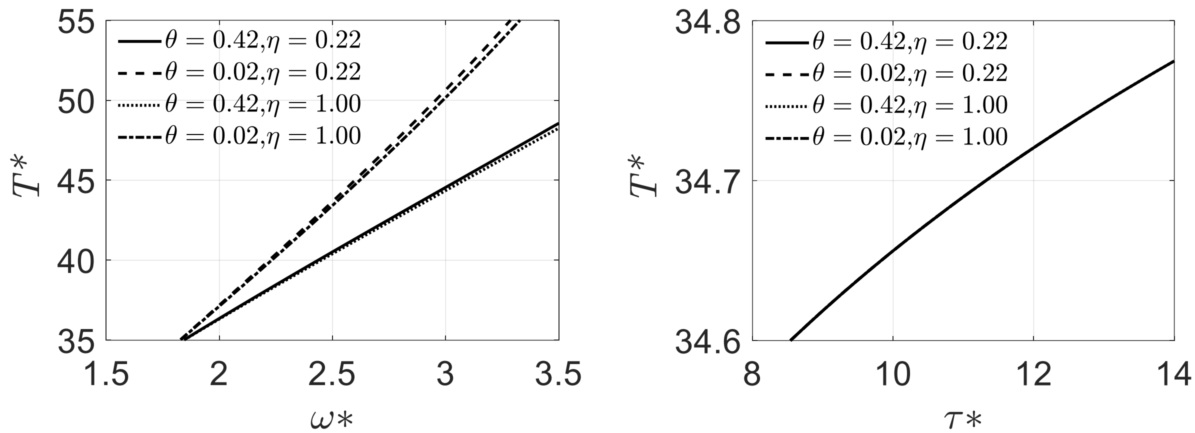

Figure caption: Subgame perfect equilibrium strategies (Case 3) given shifts of the carbon storage parameters (η, θ) with carbon sequestration benefits internalized (left) and with external carbon sequestration benefits (right). Higher carbon prices (p_c) raise the planner's tax rate (ω^*or τ^*), generating the landowner's best response T^*.

3.5. Discussion and conclusion

The main contribution of our research was to formally model and analyze the joint determination of optimal forest taxes and investments in risk reduction activities when carbon benefits are either internalized by the landowner or not. Our numerical analysis showed that when carbon benefits are internalized by the landowner, the planner's optimal tax policy adheres to the Ramsey rule and only uses the area-based tax, thus minimizing distortionary effects on the rotation age. This finding is aligned with the result from Koskela and Ollikainen (2003). However, we generalize their findings by showing that when the frequency of fires experienced by a landowner is endogenously determined by the present value of tax receipts and carbon benefits are privately internalized, land taxes levied on a per-acre basis are first-best optimal, even in the presence of an exogenous revenue target. This is because tax receipts are raised to fund public expenditures on risk mitigation, which raises a landowner's tax liability but also directly benefits the private landowner via a reduction in their risk-adjusted discount rate. We also found that when managing for carbon benefits is not internalized by landowners, the use of a yield tax is preferred to a mix of two tax instruments. However, our results suggest that the yield tax is not an effective Pigouvian instrument and the resulting equilibrium is second-best optimal. As a result, when the planner is constrained to using a yield tax instead of alternative incentives to lengthen the optimal rotation age, the planner is unable to achieve as high of a land value for the society as what can be achieved if the benefits of carbon sequestration are privately internalized by the landowner.

More general policy conclusions relate to the tradeoffs between carbon offset markets and forest-based taxes as an instrument for producing environmental amenities. A planner seeking a Pigouvian effect on the forest rotation age in carbon-productive, fire-prone regions (such as those in western Oregon) can do so either through an increase in the carbon price or through an increase in the harvest tax rate (such as the FPHT). However, if carbon prices cannot be internalized by landowners via a carbon offset market, our model finds that the capacity for the FPHT to achieve the socially optimal outcome is limited. State forest planning agencies do not currently regulate the availability of carbon credits, and so have no ability to affect the prevailing price of carbon offsets. Therefore, the FPHT rate is an alternative but imperfect mechanism for producing a higher level of carbon sequestration since it affords risk reduction and lengthens a landowner's the rotation age. The FPHT mechanism is not effective at achieving the Pigouvian solution since there is only a small distortionary effect of a higher tax rate on the landowner's rotation age. However, a simultaneous increase in the carbon offset prices can reinforce a longer rotation age. Therefore, agency planners may need to consider the effect of high carbon credit prices resulting from the scarcity of tradable permits in carbon offset markets.

This paper also shows that the optimal tax rates depend on the effectiveness of risk mitigation expenditures in terms of their ability to reduce the frequency of fire disturbances. To reduce our uncertainty about the possible values of this parameter, we conducted a simple model calibration exercise to approximate the output elasticity of risk mitigation implied by current management conditions under two alternative climate scenarios: 1) a high-frequency, low-severity fire regime, and 2) a low-frequency, high severity fire regime. We find that under the frequent fire regime, a 10 percent increase in annual risk mitigation expenditures reduces fire frequency between 1.4 and 6.1 percent. Under the low-frequency regime, a 10 percent increase in annual risk mitigation expenditures reduces fire frequency between 1.1 and 3.1 percent. These parameters suggest decreasing returns to scale from the planner's investment in risk mitigation, indicating that there is diminishing marginal productivity of risk mitigation effort. However, we restrict our interpretation of this elasticity to the management conditions specific to Douglas-fir stands subject to wildfire risk in western Oregon where the state's primary mechanism for reducing risk is an aggressive wildfire suppression response. Further research may be needed to develop more general estimates of the output elasticity of risk mitigation at regional or national scales. This parameter may find broader applications for use in public budgeting models or other numerical analyses of endogenous forest fire risk.

The optimization model in this paper makes several simplifications compared to the real-world policy environment. First, assumptions can be relaxed about the nature of the fire arrival rate. Future modeling efforts may consider the possibility for the fire arrival rate to increase on the forest stand over time. Second, assumptions can be relaxed to incorporate the possibility for private landowners to explicitly undertake risk mitigation decisions by managing hazardous fuel loads and altering the fire arrival rate of their stand. Third, assumptions should be relaxed about the possibility of salvage harvest. Salvage possibilities are likely to raise land values since a larger expected salvageable portion of the timber stand will lengthen the rotation age (Reed, 1984; Amacher et al., 2005). Fourth, we have assumed risk neutral decision-making of both the landowner and the planner. Risk aversion of a landowner can lead to more frequent turnover of forestland (Alvarex and Koskela, 2007). In cases where the planner administering fire suppression is risk averse, there may be additional public spending on risk mitigation beyond the socially optimal level (Rossi and Kuusela, 2020).

Fifth, with the planner's credible commitment to a tax policy, discretionary changes in the tax policy cannot be anticipated by the landowner or internalized into the landowner's valuation problem. The potential for time-varying changes in tax and suppression policy to be internalized into the landowner's decision calculus may render time-varying policy rules ineffective at achieving revenue targets or socially optimal Pigouvian responses. Sixth, we have omitted several information problems that may constrain the planner's decision about optimal tax policy. Specifically, we have omitted the possibility for high-risk and low-risk landowners and for this information to be knowledge exclusive to only the landowner. Admitting these information constraints into the first-stage optimization problem may transform the sequential equilibrium outcome. Specifically, incentive-compatibility and policy participation constraints may induce landowners to reveal their risk type and for the planner to differentiate tax and suppression or fuel reduction policy across landowners of different risks. Finally, we have assumed land use change as exogenous and so we have ignored the potentially distortionary effects of land value taxes as they relate to a landowner's decision to sell land off to a non-forest use. The effects of forest taxes on land use change (particularly in this setting where disturbance risk is present and carbon sequestration has value) represents an important area for further research.

Appendix A: Formulation of the Forestland Value Equation

This appendix gives the numerical expression for the landowner's objective function in equation (4). Since stand destruction is a random variable, the effective discount factor is random. Reed (1984) and Englin et al. (2000) show that the expected bare land value is written as:

$$V(T) = \frac{\mathrm{E}[e^{-rX}Y(X,T)]}{1-\mathrm{E}[e^{-rX}]} - \frac{\omega}{r}$$

Recalling that the probability density function for a Poisson distributed random variable X is $f(x) = \lambda(y)e^{-\lambda(y)x}$, the denominator simplifies to:

$$1 - \mathrm{E}[e^{-rX}] = 1 - \int_0^{\infty} e^{-rx} f(x)dx = \frac{r\left(1 - e^{-(r+\lambda(y))T}\right)}{r + \lambda(y)}$$

The numerator can be written as follows:

$$\mathrm{E}[e^{-rX}Y] = \int_0^{\infty} e^{-rx} Y(x,T) f(x)dx = \int_0^{T} e^{-rx} Y_1(x,T)\, f(x)dx + e^{-rT} Y_2(T)\, \mathrm{Pr}(X = T)$$

Recall: $\mathrm{Pr}(X = T) = e^{-\lambda(y)T}$. So the numerator is written as:

$$\mathrm{E}[e^{-rX}Y] = \int_0^T e^{-rx}\left(e^{rx}p_c k\int_0^x F'(z)e^{-rz}dz - p_c k\eta F(x) - c_0 e^{rx}\right)\lambda(y)e^{-\lambda(y)x}dx$$

$$+ e^{-rT}\left[(p-\tau-c_h)F(T) + e^{rT}p_c k\int_0^T F'(t)e^{-rt}dt - p_c k(1-\theta)F(T)\right.$$

$$\left. - c_0 e^{rT}\right]e^{-\lambda(y)T}$$

Applying integration by parts:

$$\mathrm{E}[e^{-rX}Y] = \int_0^T e^{-rx}\left[p_c k e^{rx}\left(e^{-r(x)}F(x) + r\int_0^x F(z)e^{-rz}dz\right) - p_c k\eta F(x)\right.$$

$$\left. - c_0 e^{rx}\right]\lambda(y)e^{-\lambda(y)x}dx$$

$$+ e^{-(r+\lambda(y))T}\left[(p-\tau-c_h)F(T) - c_0 e^{rT} - p_c k(1-\theta)F(T)\right.$$

$$\left. + p_c k e^{rT}\left(e^{-rT}F(T) + r\int_0^T e^{-rt}F(t)dt\right)\right]$$

We therefore have a full expression for the landowner's objective function in equation (4):

$$V(T) = \frac{r+\lambda(y)}{r\left(1-e^{-(r+\lambda(y))T}\right)}\left\{e^{-(r+\lambda(y))T}[(p-\tau-c_h)F(T) + p_c k\theta F(T)] - c_0\right.$$

$$+ rp_c k\left[\lambda(y)\left(\int_0^T e^{-\lambda(y)x}\left(\int_0^x e^{-rz}F(z)dz\right)dx\right.\right.$$

$$\left.\left.\left. + \int_0^T (1-\eta)e^{-(r+\lambda(y))x}F(x)dx\right) + e^{-\lambda(y)T}\int_0^T e^{-rz}F(z)dz\right]\right\} - \frac{\omega}{r}.$$

Appendix B: Formulation of the Expected Longrun Harvest Tax Rate

Find the tax rate required to finance a given annual suppression costs: $\tau = \tau(y, \lambda(y), T^*)$. Following Reed (1984), the long-run expected present value of harvest tax receipts is:

$$\frac{\mathrm{E}[e^{-rX}\tau F(X)]}{1 - \mathrm{E}[e^{-rX}]}. \tag{B.1}$$

The denominator of (B.1) is as in Appendix A. Recall: $f(x) = \lambda e^{-\lambda x}$ and $\Pr(X = T) = e^{-\lambda T}$. Then the denominator of (B.1) can be written as:

$$1 - \mathrm{E}[e^{-rX}] = 1 - \int_0^\infty e^{-rx} f(x)dx = \frac{r\left(1 - e^{-(r+\lambda(y))T}\right)}{r + \lambda(y)} \tag{B.2}$$

The numerator of (B.1) is:

$$\mathrm{E}[\tau F(X)] = \tau F(T)\Pr(X = T) = \tau F(T)e^{-(r+\lambda(y))T}. \tag{B.3}$$

Re-writing (B.1) using the expressions in (B.2) and (B.3), we have:

$$\frac{\mathrm{E}[e^{-rX}\tau F(X)]}{1 - \mathrm{E}[e^{-rX}]} = \frac{\left(r + \lambda(y)\right)e^{-(r+\lambda(y))T^*}\tau F(T^*)}{r\left(1 - e^{-(r+\lambda(y))T^*}\right)}.$$

Therefore the present value of forest tax revenues in equation (5) is:

$$\frac{\left(r + \lambda(y)\right)e^{-(r+\lambda(y))T^*}\tau F(T^*)}{r\left(1 - e^{-(r+\lambda(y))T^*}\right)} + \frac{\omega}{r}.$$

So, we can rearrange the planner's budget constraint from equation (5) to find the tax rate needed to raise enough funds to cover annual investment in fire risk mitigation: $\tau = \tau\left(y, \lambda(y), T^*(y)\right)$.

$$\tau\left(y, \lambda(y), T^*(y)\right) = \left(\frac{\left(r + \lambda(y)\right)e^{-(r+\lambda(y))T^*}F\left(T^*(y)\right)}{1 - e^{-(r+\lambda(y))T^*(y)}}\right)^{-1}(y - \omega + rG).$$

Appendix C: Formulation of the Planner's Budget Constraint

The budget constraint for fire suppression expenditures is:

$$\gamma_1 \frac{\mathrm{E}[e^{-rX}\tau F(X)]}{1-\mathrm{E}[e^{-rX}]} + \gamma_2 \frac{\omega}{r} = \frac{y - g_o}{r} \tag{C.1}$$

The parameter g denotes the exogenous funds allocated to fire prevention (i.e. funds raised from a non-forest tax base such as a state's general tax fund). The parameters γ_1 and γ_2 give the fractions of each forest tax raised for the purposes of fire suppression. These parameters make it explicit how much forest tax revenue is flowing to other sources outside of fire suppression or the non-forest sector. An additional constraint expresses how much money is needed from the forest sector to fund exogenous public expenses $\bar{R}$:

$$\bar{R} = (1-\gamma_1)\frac{\mathrm{E}[e^{-rX}\tau F(X)]}{1-\mathrm{E}[e^{-rX}]} + (1-\gamma_2)\frac{\omega}{r} \tag{C.2}$$

Factor out the terms in the 2nd constraint (C.2) and re-arrange:

$$\gamma_1 \frac{\mathrm{E}[e^{-rX}\tau F(X)]}{1-\mathrm{E}[e^{-rX}]} + \gamma_2 \frac{\omega}{r} = \frac{\mathrm{E}[e^{-rX}\tau F(X)]}{1-\mathrm{E}[e^{-rX}]} + \frac{\omega}{r} - \bar{R}$$

Notice the left-hand side is the same as constrain (C.1), so we can write:

$$\frac{\mathrm{E}[e^{-rX}\tau F(X)]}{1-\mathrm{E}[e^{-rX}]} + \frac{\omega}{r} - \bar{R} = \frac{y}{r} - \frac{g_o}{r}.$$

Define $\bar{G} = \frac{\bar{R}-g_o}{r}$. This gives the relevant budget constraint presented in equation (5).

$$\frac{\mathrm{E}[e^{-rX}\tau F(X)]}{1-\mathrm{E}[e^{-rX}]}+\frac{\omega}{r}=\frac{y}{r}+\bar{G}.$$

Therefore, $\bar{G}$ represents the [exogenous] present value of the sum of all other annual revenue requirements (other expenditures) minus suppression funding collected from other sources. If tax revenues are needed to fund non-forest related public expenditures, then $\bar{G}$ goes up. If more funding is collected for suppression (e.g. from the General tax fund), then $\bar{G}$ goes down.

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CHAPTER 4: A MICROECONOMETRIC ANALYSIS OF FIRE SUPPRESSION DECISIONS IN THE WESTERN UNITED STATES

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4.1. Introduction

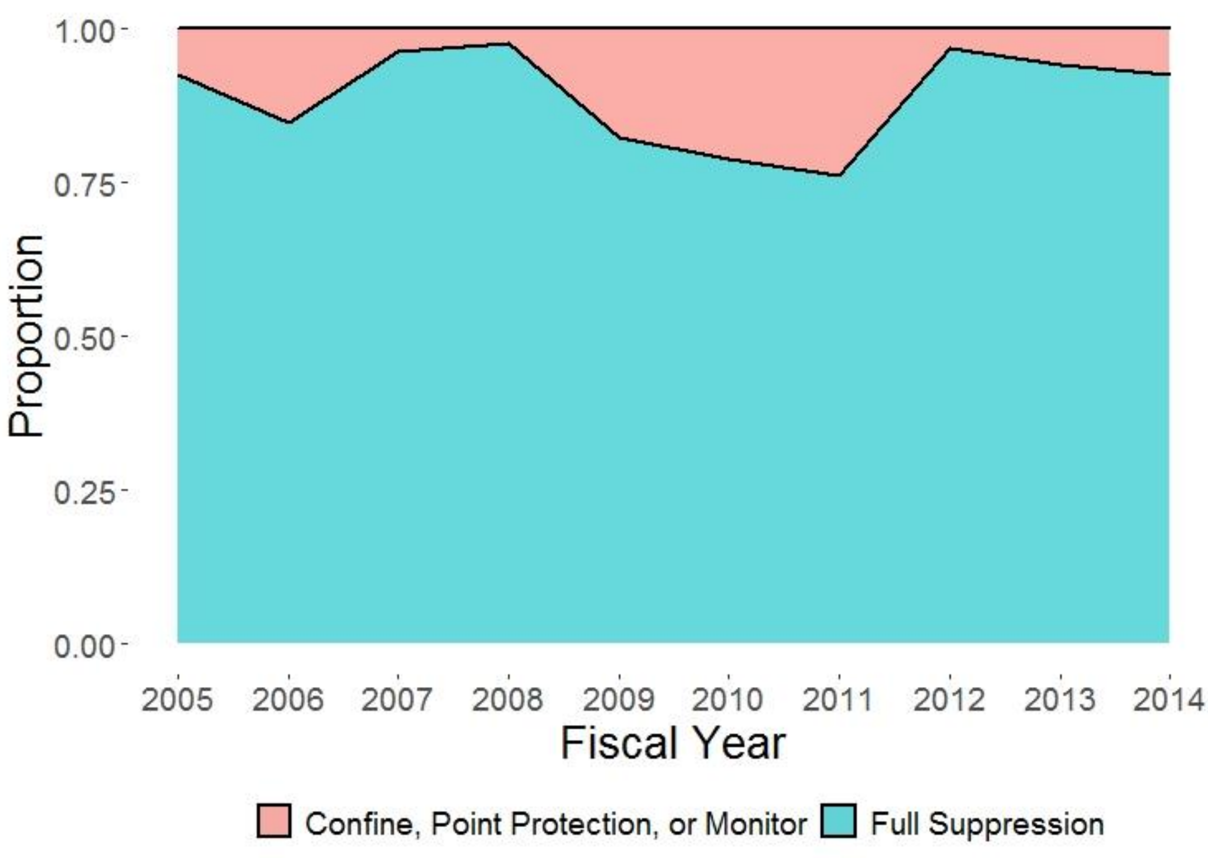
Wildfire suppression expenditures have become an increasingly visible source of costs for public land management agencies in the United States since the mid-1980s as burned acreage, damages, and public expenditures on suppression are increasing (Lueck and Yoder, 2013). While climatic factors and daily changes in weather patterns contribute to increasing fire severity (van Mantgem et al., 2013), they are not the sole driver of these trends. Socioeconomic factors and institutional factors can also impact the decisions made by wildfire incident managers including their increasing reliance on an aggressive suppression response (Schultz et al., 2019; Thompson, 2014). The primary concern with a continued pattern of aggressive suppression response is the formation of a "fire paradox" (Thompson et al., 2013; 2018; Calkin et al., 2015), whereby the exclusion of wildfire from western U.S. forests can allow hazardous fuels to accumulate, leading to larger fires and exacerbating the need for future suppression effort.

Annual growth in fire size has averaged 30% per year since 1980, while federal expenditures on fire suppression in 2020 totaled $2.27 billion and encompassed 68.8% of annual fire management expenditures in the U.S. Forest Service (36.3% of its total budget). A less aggressive suppression response and the management of unplanned wildfires for resource benefits (referred to as "wildfire use")[30] is anticipated to bring down suppression costs over time by reducing fire size and severity (North et al., 2012; Ingalsbee and Raja, 2015). Despite a now widespread recognition for the need to re-introduce fire on western landscapes via prescribed fire and wildfire use (WFLC, 2009; 2014; FMB, 2019), suppression strategies still dominate both federal and state agencies' approach to wildfire emergency response (North et al., 2015). From 1998 to 2008, an annual average of 0.42% of wildfires were managed as "fire-use" events, but

[30] https://www.fws.gov/fire/what_we_do/wildland_fire_use.shtml

reporting of this percentage was halted in 2009 after an alternative definition of "fire use" acreage burned was adopted by federal agencies (Stephens et al., 2016).[31] Figure 4.1 shows the annual percentage of daily reports filed by incident managers in the SIT-209 system in California, Oregon, and Washington from 2005 to 2014. Most of these forms (90.8%) report a "full suppression" strategy as the chosen response. The remaining forms report a less aggressive response to fire management, which may include a strategy of "confining" a wildfire to defined area, "point protection" of values at risk, or a "monitoring" strategy which entails limited suppression effort and a willingness to let a fire run its course.

Figure 4.1 - Annual Suppression Strategies reported in ICS-209 Forms (California, Oregon, and Washington, FY2005-FY2014)



[31] https://www.nifc.gov/fireInfo/fireInfo_stats_fireUse.html

Each of these response strategies to wildfire entail a different use of suppression resources and thus a different management cost. Confinement strategies attempt to restrict a fire to a defined area by using a combination of natural and constructed barriers which are anticipated to limit fire spread (USFS, 2013). Point or zone protection strategies seek to limit fire spread in a residential community, over an individual structure, a communication site, or a highly-valued resource area or cultural site (USFS, 2013). As such, point protection is primarily a defensive strategy; seeking to defend resources from damage rather than attempt to extinguish an ongoing blaze. Monitoring specifically entails the process of "observing, collecting, and recording of fire-related data… for the purpose of determining if management objectives are being met" (USFS, 2013). A monitoring response does not seek to actively extinguish a fire or limit its spread in any way. In stark contrast to these three strategies, a full suppression strategy entails an attempt to "put the fire out" as efficiently and effectively as possible (USFS, 2013). While the fire management literature has not formally addressed the relationship between full suppression strategies as recorded in the SIT-209 forms and suppression expenditures or resource demand, the adoption of full suppression strategies typically entails greater expenditures and a greater number of resources committed to the incident. For example, a dataset consisting of 139 fires across Oregon and Washington from 2012 to 2013 indicates that monitoring strategies cost an average of $25,778 per fire; point protection strategies cost $218,247 per fire; confinement strategies cost $1.76 million per fire; while full suppression strategies cost $5.24 million per fire (NWCC, 2013; 2014).

Some papers have attempted to measure the effects of socioeconomic and institutional factors on the demand for suppression resources (e.g. Hand et al., 2017) or on suppression costs (e.g. Donovan et al., 2011; Liang et al., 2008), but none have analyzed the joint significance of such effects on observed variations in manager choices regarding suppression response. To address this gap in the literature, this paper provides an econometric analysis of individual suppression decisions to measure the relative influence that socioeconomic and institutional factors have on the probability of choosing a "full suppression" strategy. We especially are interested in whether socioeconomic factors have a greater or lesser influence on observed suppression choices before or after a major change in the budgetary institution governing the use of suppression tactics and the allocation of suppression funding. Administrative data is obtained and compiled to track the daily suppression strategies adopted by publicly-contracted and agency-employed incident managers fighting wildfires for state and federal land management agencies in the western U.S. from July of 2005 to November of 2013. Estimated parameters of a binary choice model are used to recover an estimate of the relative marginal effects of socioeconomic and institutional factors that drive suppression decisions and to determine if these factors have a greater or lesser impact on suppression choices following a change in fire management legislation.

One key piece of fire management legislation passed during this period was the Federal Land Assistance, Management and Enhancement (FLAME) Act of 2009. This legislation encouraged federal land managers to more actively adopt strategies which allow unplanned wildfire events to burn when spread conditions are safe. This was echoed in the February 2009 Guidance for Implementation of the Federal Wildland Fire Management Policy (WFLC, 2009b). This guidance enabled incident managers for the first time to update the strategy applied to an ongoing wildfire which was initially managed under a full suppression strategy. Following a recommendation from the GAO (GAO, 2004), the act also provided an additional set of reserve funds available for fighting wildfires when annual appropriations were depleted. These funds were available upon request to both federal and state incident managers from FY2010 to FY2017 with the approval of the Secretary of the Interior or the Department of Agriculture. In fiscal year 2017, FLAME funds were not subject to discretionary spending caps, and the Forest Service eventually requested emergency funding for the FLAME accounts beyond that year's appropriations. The Forest Service also retained the authority to request re-imbursement for FLAME funds that are used to repay funds borrowed from non-fire accounts. This means that the Flame Act reserve funds enabled agencies to retain the ability to draw from non-fire accounts to finance suppression efforts, replenish those accounts with FLAME reserve funds, then request that Congress re-imburse the borrowed FLAME funds (Hoover and Lindsay, 2017). To prevent this practice, the Consolidated Appropriations Act of 2018 has set up a similar set of reserve accounts, but it has increased the size of these accounts by more than 1000 percent. Reserve appropriations and off-budget financing has been replaced by an increase in budget authority, without regard to a shift in manager incentives to lower suppression costs. This raises questions about whether these past revisions in legislation which have introduced reserve funding have actually achieved a containment of suppression program costs.

The contribution of our research is to measure the effects of the FLAME Act's implementation on suppression choices amongst state and federal land management agencies. The FLAME Act of 2009 and the accompanying 2009 policy guidance (WFLC, 2009b) encouraged greater adoption of wildfire-use strategies on federal lands while at the same time set up a reserve account for emergency suppression funding. The net effects of this policy change on suppression choices has not been examined using observational data. One exception is Young et al. (2020) who use incident-level data and found that the 2009 fire policy guidance (WFLC 2009b) served to decrease the number of fires managed solely under a full suppression strategy by an estimated 27% to 73%, but found limited effects of the policy on the duration and size of fires across four major regions of the U.S. (Western U.S., Inland Empire, Southwest, and the Rocky Mountains). This paper estimates linear and nonlinear probability models to measure the effects of the 2009 fire policy guidance and the FLAME Act's implementation across state and federally managed wildfire incidents in the western U.S., and across varying distances from residential values at risk. Our estimates of the average partial effect of socioeconomic factors are allowed to differ before and after the FLAME Act and are compared across the pooled nonlinear probability models and linear probability models which account for unobserved characteristics of incident managers. We generally find consistency of these results across model specifications and show that while the FLAME Act had the effect of decreasing the overall probability of adopting a full suppression response, but this effect is indistinguishable from the effects of the 2009 policy guidance. Further, its effects on adoption differed across state and federally managed incidents and serve to either diminish or enhance the effects of some socioeconomic factors that influence suppression decisions (especially the incident's distance from residential values-at-risk). While the FLAME Act successfully achieved its goal of increasing the adoption of fire use strategies for federally managed incidents, it had the opposite effect on incidents managed by state agencies. Additionally, the nonlinear probability models find that the probability of adopting an aggressive suppression response decreases for incidents occurring at larger distances from residential values-at-risk but is larger following the implementation of the FLAME Act. Overall, we find evidence that socioeconomic factors are statistically significant drivers of wildfire suppression response, but that climatic factors like humidity have a much larger effect on choices.

The remainder of this paper is organized as follows. First, we discuss the literature on the influence of socioeconomic and institutional factors on the suppression decisions of wildfire management agencies, including the influence that FLAME Act reserve funds may have had on suppression choices. Second, we present a theory of discrete choice which allows us to identify factors exogenous to manager suppression decisions. Third we present and estimate a suite of binary choice models to measure the influence of these exogenous factors on observed suppression decisions and conduct a Chow test of structural change across pre- and post-FLAME Act periods (Chow, 1960). We then discuss results and policy implications before identifying directions for further research.

4.1.1. Review of socioeconomic and institutional factors affecting suppression decisions

Empirical evidence has found that factors unique to an incident manager contracted or employed to oversee a wildfire event can significantly impact the demand for suppression resources. These differences are attributed to differences in risk attitudes (Hand et al., 2017). Specifically, these risk attitudes may refer to differences in manager risk aversion or differences in downside risk aversion (Rossi and Kuusela, 2020). Downside risk aversion refers to a manager's preference for right-skewed payoff distributions, assuming all other moments of any two payoff distributions are held constant. Rossi and Kuusela (2020) show that when suppression effort increases the skewness of the payoff distribution (as is typical during incidents close to human populations or valuable residential development), we should expect to see greater demand for suppression effort. However, when suppression lowers the skewness of the payoff distribution (which is more common when fires burn farther from residential development), suppression demand falls. Additional empirical evidence on a sample of fires in the western U.S. from 2003 to 2010 found that proximity of fires to high-valued residential developments can significantly influence the demand for firefighting resources (Bayham and Yoder, 2020). Therefore, we should expect to see incident managers adopt a more aggressive suppression strategy when fires are closer to the wildland-urban interface where there is a high value of assets at risk and adopt less aggressive strategies when fires burn farther from these areas.

Studies have also suggested that the complexity of a wildfire incident (characterized by competing management objectives, time-pressured decision environments, high fire severity, irregular topography, fragmentation of land tenure, and value-at-risk) can impact a manager's choice of suppression strategy (Maguire and Albright, 2005; Holmes and Calkin, 2013). This complexity can lead to an increased likelihood of shorter fire durations (due to an adoption of more aggressive suppression response; Thompson, 2013). These types of incidents are managed by "high complexity" incident management teams (Type 1 or Type 2 teams). Cullen et al. (2020) present the results of a probability model estimated using daily time series data and find that incident complexity can be a significant factor used for predicting suppression demand. In their model, total resource demand is defined as a dichotomous variable, found by splitting the national preparedness level into "high preparedness" (levels 4 and 5) and "low preparedness" (levels 1, 2, and 3). Predictions of the demand for suppression resources at the national scale find that the number of Type 2 incidents increase the probability of high resource demand by 0.04 to 0.5 probability points while the number of Type 1 incidents increase the probability of high demand by 0.63 to 0.67 probability points (Cullen et al., 2020). These effects are much larger for models of resource demand in the Pacific Northwest states of Oregon and Washington (0.125 to 0.137 for the number of Type 2 incidents and 0.102 to 0.136 probability points for the number of Type 1 incidents). Other studies have investigated the behavioral aspects of highly complex incidents, suggesting that decision biases or satisficing behavior may be prevalent during complex and time-pressured decision environments (Wilson et al., 2011; Wibbenmeyer et al., 2013; Hand et al., 2015; Rossi and Kuusela, 2019; Wibbenmeyer et al., 2019). These biases can lead to a larger demand for suppression effort in an attempt to meet management objectives.

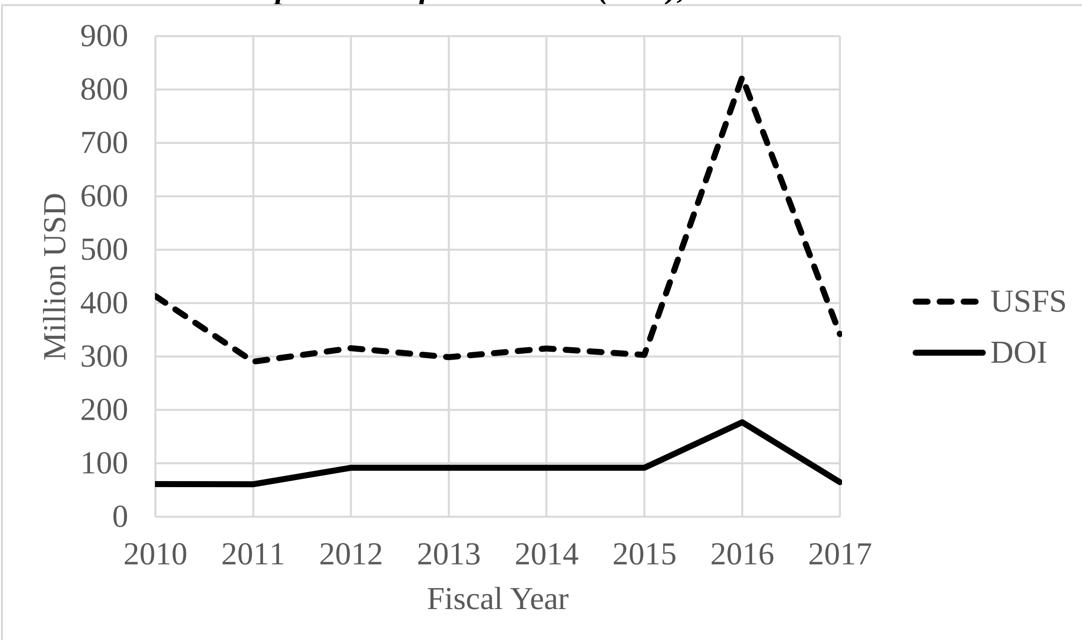
"Budgetary institutions" are the rules, norms, and legal precedents that govern the allocation of scarce public budgets (Von Hagen, 2007; Raudla, 201). The fire management literature has identified two forms of institutional rules which are hypothesized to influence manager suppression choices: 1) "let-burn" policies which vary across state and federal jurisdictions and which relate to the cause of a wildfire ignition (Young et al., 2020), and 2) reserve funding mechanisms for wildfire suppression (Ingalsbee, 2010).

With regard to let-burn policies, an important goal of the National Cohesive Wildfire Management Strategy (WFLC, 2009a) was to re-enforce the possibility for land management agencies to effectively engage in strategies that allow wildfires to burn in order to capture benefits to fire-dependent natural resources (North et al., 2015). This policy was reinforced through the guidance and implementation of the 2009 FLAME Act (WFLC, 2009b). Prior to the development of this policy, agencies had little authority to adopt strategies that allowed wildfires to burn in order to capture benefits to natural resources. While it is more feasible for federal land management agencies to adopt "let-burn" strategies, state and local land management agencies face intense pressure to aggressively suppress wildfire. This is due primarily to statutory constraints at the state level, driven primarily by the fact that state agencies rely heavily on revenue from resource extraction and recreation. Additionally, state agencies manage more fragmented land holdings, which are often intermixed with areas of private lands, rendering a less aggressive suppression strategy infeasible. For example, in Oregon, all wildfires are to be kept to the smallest possible size and full suppression strategies are always to be adopted by incident managers (ODF, 2017). Despite these differences across federal and state agencies, it is also possible that federal agencies have not adequately taken advantage of this flexibility in wildfire policy (North et al., 2015; Thompson et al., 2017), rendering no true difference in the probability of adopting an aggressive suppression response across federal and state agencies before and after the implementation of the FLAME Act.

A related budgetary institution that may influence suppression choices is the inter-agency rule regarding the management of human-caused ignitions under a “let-burn” strategy. Federal policy guidance stipulates that “initial action on human-caused wildfires will be to suppress the fire at the lowest cost with the fewest negative consequences with respect to firefighter and public safety” (WFLC, 2009b). Research has shown that the daily percentage of human-caused ignitions can be an important predictor of the demand for suppression resources and the national wildfire preparedness level, although the magnitude of the effect of human caused ignitions is uncertain (Cullen et al., 2020). “Saturated” linear probability models and logistic regression models (which use an unrestricted set of covariates) estimated using national data find a *positive* effect of human-caused ignitions on the preparedness level, while “information-rich” linear models (which use a restricted set of covariates) estimated using data from the Pacific Northwest and “information rich” logistic regression models estimated using national data find a *negative* effect of human-caused ignitions on the preparedness level (Cullen et al., 2020).

Another important institutional factor driving suppression decisions is the budgeting practices which direct fire management funding (Donovan and Brown, 2005; Donovan et al., 2008; Rossi and Kuusela, 2019). Budgeting institutions define the rules over how public programs are funded and create norms about the use of these funds within a public agency (Von Hagen, 2007; Raudla, 2014). A primary example of such a mechanism was the annually appropriated reserve accounts set up under the Federal Land Assistance, Management, and Enhancement (FLAME) Act of 2009. This legislation set up an additional account at the U.S. Treasury to be filled annually and used for wildfire suppression only under an emergency declaration. These declarations were only to be made on fires exceeding 300 acres or when annual appropriations were expected to be depleted over the next 30 days (Hoover and Lindsay, 2017). The FLAME Act reserve funds were intended to diminish the need for agencies to borrow from non-fire accounts and for requesting off-budget funding (Hoover and Lindsay, 2017). The funds were annually budgeted for and allocated to federal land management agencies from Fiscal Year 2010 to Fiscal Year 2017 (see Figure 4.2). These accounts were distinguished from non-appropriated supplementary funds allocated for fire suppression "as needed" throughout the fiscal year. During the period when FLAME funds were annually appropriated, agencies could access supplementary off-budget funding only after depleting annual Wildfire Management (WFM) appropriations plus annual FLAME reserve appropriations. This extra step required for accessing additional suppression funds was intended to encourage fiscal discipline with regard to wildfire suppression expenditures (Hoover and Lindsay, 2017).

Figure 4.2 - Annual FLAME Fund Appropriations to the U.S. Forest Service (USFS) and U.S. Department of the Interior (DOI), FY2010-FY2017.



However, in 4 of 8 years from 2010 to 2017, the FLAME funds were completely exhausted, rendering the need for additional off-budget financing. One stipulation on the use of the FLAME funds that may have contributed to this tendency to exhaust the FLAME funds is the regulatory rule regarding the termination of authority over the use of the FLAME funds (43 U.S. Code § 1748a). This rule requires the secretary of the overseeing agency to terminate the FLAME fund following three consecutive years without the agency's withdrawal from the fund (or Congress's appropriations into the fund). This may lead to a perverse incentive for fire managers to more frequently respond to wildfire with aggressive suppression tactics to avoid the removal of FLAME accounts in later years where wildfire activity is especially severe.

In addition to this perverse incentive, economic models of suppression demand have demonstrated how the availability of additional funding above initial annual appropriations essentially serves to lower the effective marginal cost of suppression effort (Donovan and

Brown, 2005; Rossi and Kuusela, 2019), leading to an increased demand for suppression and a larger proportion of annual expenditures devoted to suppression programs in lieu of pre-suppression programs (Rossi and Kuusela, 2019). The availability of reserve funds may be used to refill non-fire appropriated accounts that have been tapped to fund wildfire suppression, leading to an overall increase in suppression expenditures and a disruption in the funding available for non-fire related land management programs (Ingalsbee, 2010). This arises from the treatment of suppression reserve funds as a common pool resource, leading to depletion of the reserve funding pool as the effective marginal cost of funds to each user is diminished (Raudla, 2014).

The FLAME funds have been unfilled each year beginning in Fiscal Year 2018. However, the extent to which these funds were useful in implementing a more or less judicious use of annual WFM appropriations has been unaddressed in the fire management literature. Expenditure data available from the National Interagency Fire Center[32] and resource demand data obtained from the Resource Ordering and Status System[33] (ROSS) suggest that both suppression expenditures and the demand for some suppression resources increased in the years following the creation of the FLAME reserve accounts (see Table 4.1). We note a larger demand in higher cost suppression resources like air resources and ground crews during the post-FLAME years, although we see almost no change in average daily demand for bull dozers and a decline in average daily demand for fire engines. The availability of the FLAME funds or similar reserve funds may have an impact on suppression activity by measures of costs or resource demand, but whether the availability of these funds encouraged more frequent or less frequent "full

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[32] https://www.nifc.gov/fireInfo/fireInfo_documents/SuppCosts.pdf

[33] Air Resources are defined as all Large Airtankers, Smaller Aircraft, Type 1, Type 2 and Type 3 Helicopters. Ground Crews include all Type 1, Type 2, and Type 2 Initial Attack Crews or other crews utilized for low complexity incidents.

suppression" responses is not clear. No study, to date, has empirically estimated the impact of access to FLAME funds on suppression decisions or distinguished the effects of the FLAME Act from the 2009 fire policy guidance. This paper addresses this gap in the literature and provides additional evidence on the effects of other institutional and socioeconomic factors on suppression decisions in the western United States.

Table 4.1 – U.S. Suppression Expenditures and Resource demand in western U.S. across pre- and post-FLAME Act years

	Pre-FLAME years (FY2002-FY2009)	Post-FLAME years (FY2010-FY2017)
Average Annual U.S. Federal Agency Suppression Expenditures*	USFS: $984.8 million DOI: $347.5 million	USFS: $1.42 billion DOI: $379.8 million
Average Daily Demand for Suppression Resources in the U.S.**	Air Resources: 42.2 Bull Dozers: 22.9 Fire Engines: 24.7 Ground Crews: 36.9	Air Resources: 52.3 Bull Dozers: 22.7 Fire Engines: 11.6 Ground Crews: 40.2
Percentage of ICS-209 reports recording a "full suppression" strategy in OR, WA, and CA***	91.5%	89.5%

*Includes all annual appropriates + FLAME Act reserve funds + additional supplementary appropriations. Figures exclude state agency suppression expenditures. Source: NIFC.
**Data for year 2006 is not available, so pre-FLAME data reflects resource demand from January 2007 to September of 2009.
***Sample data only available from June 2005 to December 2013.

4.2. Random utility model

We start with the continuous effort s_{jt} demanded by an incident manager j observed at date t. Managers seek to maximize their utility $U_{jt}(\cdot)$ while meeting a budget constraint by selecting the optimal effort level s_{jt}^{*}. The following expression (3.1) characterizes an incident manager's indirect utility following this demand for suppression:

$$V_{jt}^{*}(\mathbf{w}_{jt},\mathbf{x}_{jt},\theta_{jt}) = \underset{s_{jt}\in[0,\infty)}{\text{maximize}}\{U_{jt}(s_{jt};\mathbf{w}_{jt},\mathbf{x}_{jt})\ s.t.\ C_{jt}(s_{jt};\mathbf{w}_{jt},\mathbf{x}_{jt}) \leq (1+\theta_{jt})\bar{B}_{jt}\} \tag{3.1}$$

In equation (3.1), $C_{jt}(s_{jt};\mathbf{w}_{jt},\mathbf{x}_{jt})$ is the cost of adopting suppression strategy s_{jt}. The arguments $\mathbf{w}_{jt}$ refer to exogenous climate or weather factors and the arguments $\mathbf{x}_{jt}$ refer to exogenous socioeconomic factors which effect the costs of suppression and a manger's utility. We define $\theta_{jt} \in [0,\infty)$ as the proportion of each day's available appropriations which are also available through a reserve funding mechanism. When $\theta_{jt} = 0$, all suppression expenditures are covered by available appropriations ($\bar{B}_{jt}$), but when $\theta_{jt} > 0$, reserve funding of the amount $\theta_{jt}\bar{B}$ is also available and the total suppression cost becomes: $\bar{B}_{jt} + \theta_{jt}\bar{B}_{jt}$. The envelope condition $\left(\frac{\partial V_{jt}^{*}}{\partial \theta_{jt}}\right)$ for this constrained utility maximization problem provides a direct interpretation of the parameter θ in eq. (3.1). When θ_{jt} increases, a manager's demand for suppression will increase if the budget constraint is binding. If the constraint is non-binding, an increase in the proportion of funding available through a reserve mechanism will not raise the demand for suppression.

We can now define a threshold effort level $\bar{s}$ over which managers will adopt a "full suppression" response. When $s_{jt}^{*} > s_{jt}^{o}$, then we would observe managers choose a full suppression strategy. Then, an incident manger's utility from the threshold level effort is: $V_{jt}^{o}\left(s_{jt}^{o}(\mathbf{w}_{jt},\mathbf{x}_{jt},\theta_{jt})\right) + \varepsilon_{jt}^{o}$, where ε_{jt}^{o} is a random error term which captures unobserved factors contributing to a manger's utility. If instead $s_{jt}^{*} \leq s_{jt}^{o}$, we would observe manager j select a "monitor (MN)" strategy, "point-protection (PP)" strategy, or a "confine (CF)" strategy (indicating a less-than fully aggressive suppression response since the managers utility from a full suppression response would not exceed the utility from lower suppression demand, $V_{jt}^{*} \leq V_{jt}^{o}$). Then we can write the observed suppression choice as:

$$\tilde{s}_{jt} = \begin{cases} 1 & if \text{ FS } strategy\ is\ chosen: V_{jt}^{*} > V_{jt}^{o} \\ 0 & if \text{ MN, PP,} or \text{ CF } strategy\ is\ chosen: V_{jt}^{*} \leq V_{jt}^{o} \end{cases}$$

Therefore, a probability model which isolates exogenous factors is given by:

$$\Pr(\tilde{s}_{jt} = 1 | \mathbf{w}_{jt}, \mathbf{x}_{jt}, \theta_{jt}) = \Pr(V_{jt}^{*} > V_{jt}^{o})$$

$$= \Pr\left(V_{jt}^{\star}\left(s_{jt}^{*}(\mathbf{w}_{jt}, \mathbf{x}_{jt}, \theta_{jt})\right) + \varepsilon_{jt}^{*} > V_{jt}^{o}\left(s_{jt}^{o}(\mathbf{w}_{jt}, \mathbf{x}_{jt}, \theta_{jt})\right) + \varepsilon_{ijt}^{0}\right)$$

$$= \Pr\left(\varepsilon_{jt}^{0} - \varepsilon_{jt}^{*} < V_{jt}^{\star}\left(s_{jt}^{*}(\mathbf{w}_{jt}, \mathbf{x}_{jt}, \theta_{jt})\right) - V_{jt}^{o}\left(s_{jt}^{o}(\mathbf{w}_{jt}, \mathbf{x}_{jt}, \theta_{jt})\right)\right)$$

(3.2)

With this specification, we note that the FLAME Act's implementation and the 2009 fire policy guidance may have served to increase the threshold level of suppression effort (s_{jt}^{o}) required before a manager sees the utility in adopting a full suppression response. This would decrease the probability of a manager adopting full suppression. On the other hand, it may also be that the increase in the size of the reserve suppression budget raised the marginal utility of suppression, thereby leading to more frequent adoption of a full suppression response. From this specification, it is not clear *a priori* which of these two effects dominates. We therefore require an empirical estimation of the choice probability equation to draw inference about the magnitude and direction of this effect from the policy change.

4.2.1. Specifications of the probability equation

A benchmark econometric analysis of binary choice data on suppression strategies can begin with a pooled linear probability model (LPM), which is valid for conducting classical inference of average partial effects (Cameron and Trivedi, 2005, Ch. 14). We denote each report filed with the subscript i and estimate the probability of adopting a full suppression response. The LPM is given in equation (3.3).

$$\Pr[\tilde{s}_i = 1|\mathbf{x}_i, \mathbf{w}_i, \theta_i] = \alpha_0 + \alpha_1 \ln wuidist_i + \alpha_2 complex_i + \alpha_3 federal_i + \alpha_4 human_i + \alpha_5 highprep_i + \alpha_6 OR_i + \alpha_7 WA_i + \gamma_0 flame_i + \gamma_1 \ln wuidist_i * flame_i + \gamma_2 complex_i * flame_i + \gamma_3 federal_i * flame_i + \gamma_4 human_i * flame_i + \gamma_5 highprep_i * flame_i + \gamma_6 OR_i * flame_i + \gamma_7 WA_i * flame_i + \mathbf{w}_i' \boldsymbol{\beta} + \varepsilon_i. \tag{3.3}$$

This paper is primarily interested in the variable $flame_i$, which is a dummy variable indicating if the ICS-209 report was filed in the pre-FALME period (FY2005-FY2009) or the post-FLAME period (FY2010-FY2014). This variable is interacted with each of the socioeconomic, weather and climate covariates to determine if these factors had a greater or lesser effect on suppression probability following the FLAME Act's implementation. These other variable definitions and summary statistics are provided in Table A.1. We assume independence in the LPM between the unobserved factors contributing to the suppression decision and the observed factors (such as ability, experience managing fires, risk tolerance, the contracting or employing agency, or the manager's dispatch location): E$[\varepsilon_i|\mathbf{x}_i, \mathbf{w}_i]$. We can interpret the γ_k individually as the partial effects of covariates in the post-FLAME Act years on the probability of choosing a "full suppression" response. Since the availability of FLAME reserve funds does not span the entire dataframe, the coefficients γ_k enable a joint hypothesis test which can be used to determine the effect of the budget intervention on the partial effects. Under the null hypothesis of a Chow test for structural change across time, the joint effects of the γ_k are zero, indicating that the FLAME Act had no significant effect on the probability of adopting a suppression strategy.

$$H_0: \gamma_1 = \gamma_2 = \cdots = \gamma_7 = 0$$

$$H_A: at\ least\ one\ of\ the\ \gamma_k \neq 0$$

(H.1)

The test statistic for (H.1) is distributed F with (N-2(k+1)) and (k+1) degrees of freedom. A rejection of the null hypothesis in test (H.1) would indicate that the policy changes created by the FLAME Act altered the effects that socioeconomic factors and climatic factors had on suppression decisions in the western United States.

Support for other alternative hypotheses can be found by subjecting the coefficients α_j to individual or joint hypotheses which, under the null, assume the population coefficients α_j are either individually or jointly no different from zero. A rejection of these null hypotheses provide evidence that socioeconomic and institutional factors impact the suppression decision. From a series of joint hypotheses, we can determine if socioeconomic factors matter jointly in determining suppression decisions. Separately, we can test the joint significance of coefficients relating weather and climate variables to suppression decisions. These tests may help to determine if socioeconomic factors or climate and weather factors were more important drivers of suppression decisions over the course of the sample period.

While valid for conducting inference of average marginal effects, the LPM (3.3) has several drawbacks, including heteroskedasticity and predicted probabilities which fall outside the [0,1] range. However, the estimated average partial effects from the linear probability model estimated using Ordinary Least Squares are consistent, and so provide a solid benchmark for comparing partial effects from alternative nonlinear models. Two commonly used nonlinear specifications include the probit model and the logit model. The probit model is:

$$\Pr[\tilde{s}_i = 1|\mathbf{x}_i, \mathbf{w}_i, \theta_i] = \Phi(\alpha_0 + \alpha_1 \ln wuidist_i + \alpha_2 complex_i + \alpha_3 federal_i + \alpha_4 human_i +$$

$$\alpha_5 highprep_i + \alpha_6 OR_i + \alpha_7 WA_i + \gamma_0 flame_i + \gamma_1 \ln wuidist_i * flame_i + \gamma_2 complex_i *$$

$$flame_i + \gamma_3 federal_i * flame_i + \gamma_4 human_i * flame_i + \gamma_5 highprep_i * flame_i + \gamma_6 OR_i * flame_i + \gamma_7 WA_i * flame_i + \mathbf{w}_i' \boldsymbol{\beta}),$$

(3.4)

where $\Phi(z)$ is the standard normal cumulative density function (CDF). The logit model is:

$$\Pr[s_i = 1|\mathbf{x}_i, \mathbf{w}_i, \theta_i] = \Lambda(\alpha_0 + \alpha_1 \ln wuidist_i + \alpha_2 complex_i + \alpha_3 federal_i + \alpha_4 human_i + \alpha_5 OR_i + \alpha_6 WA_i + \alpha_7 highprep_i + \gamma_0 flame_i + \gamma_1 \ln wuidist_i * flame_i + \gamma_2 complex_i * flame_i + \gamma_3 federal_i * flame_i + \gamma_4 human_i * flame_i + \gamma_5 highprep_i * flame_i + \gamma_6 OR_i * flame_i + \gamma_7 WA_i * flame_i + \mathbf{w}_i' \boldsymbol{\beta}).$$

(3.5)

Where $\Lambda(z)$ is the CDF of a logistic distribution.

Since the dependent variable is highly skewed (90.8 percent of the s_i take on the value of 1), estimated marginal effects may not have the greatest impact at a probability of 0.5 as they would under a symmetric probability distribution. The true probability distribution may not be symmetric since the probability of choosing suppression is very large in our sample, rendering the assumption of a symmetric probability distribution inappropriate (Chen et al., 1999). Data with this structure can impact the estimates of marginal effects since the greatest partial effect may not occur at the mean of the covariates (Nagler, 1994). We can apply a "Skewed Probit" model to conduct a simple hypothesis test which determines if this skewness is affecting the inferences drawn from the estimated coefficients (Niekerk and Rue, 2020; Chen et al., 1999). The skewed probit model is:

$$\Pr[\tilde{s}_i = 1|\mathbf{x}_i, \mathbf{w}_i, \theta_i] = \Psi(\delta, \alpha_0 + \alpha_1 \ln wuidist_i + \alpha_2 complex_i + \alpha_3 federal_i + \alpha_4 human_i + \alpha_5 highprep_i + \alpha_6 OR_i + \alpha_7 WA_i + \gamma_0 flame_i + \gamma_1 \ln wuidist_i * flame_i +$$

$$\gamma_2 complex_i * flame_i + \gamma_3 federal_i * flame_i + \gamma_4 human_i * flame_i + \gamma_5 highprep_i * flame_i + \gamma_6 OR_i * flame_i + \gamma_7 WA_i * flame_i + \mathbf{w}_i'\boldsymbol{\beta}). \tag{3.6}$$

Where $\Psi(\delta, z)$ is the CDF of a half-normal distribution and δ is a shape parameter providing a measure of the degree of skewness. If $\delta = 0$, the model collapses back to the standard Probit model in equation (3.3) (Chen et al., 1999; Lee and Sinha, 2019). If $\delta \neq 0$, marginal effects are well-approximated by a complementary log-log model, which also has an asymmetric link function (Chen et al., 1999). This model is:

$$\begin{aligned}\Pr[\tilde{s}_i = 1|\mathbf{x}_i, \mathbf{w}_i] \\ &= \Pi(\alpha_0 + \alpha_1 \ln wuidist_i + \alpha_2 complex_i + \alpha_3 federal_i + \alpha_4 human_i \\ &+ \alpha_5 highprep_i + \alpha_6 OR_i + \alpha_7 WA_i + \gamma_0 flame_i + \gamma_1 \ln wuidist_i * flame_i \\ &+ \gamma_2 complex_i * flame_i + \gamma_3 federal_i * flame_i + \gamma_4 human_i * flame_i \\ &+ \gamma_5 highprep_i * flame_i + \gamma_6 OR_i * flame_i + \gamma_7 WA_i * flame_i + \mathbf{w}_i'\boldsymbol{\beta})\end{aligned} \tag{3.7}$$

The complementary log-log model has a link function of $\Pi(z) = 1 - \exp(-\exp(z))$. The nonlinear models (3.4), (3.5), (3.6), and (3.7) are estimated using the maximum-likelihood method.

The overall effect of the FLAME Act on suppression probability is also uncertain and can be inferred from observational data based on the difference in predicted probabilities (Long and Freese, 2014) across the pre-FLAME period ($\Pr(s_i = 1|flame_i = 0)$) and the post-FLAME period ($\Pr(s_i = 1|flame_i = 1)$). On the one hand, the FLAME Act encouraged less aggressive suppression strategies on federal lands and created an additional barrier before agencies could access additional reserve funds. On the other hand, the FLAME Act reserve funds increased the size of available suppression appropriations through the creation of the reserve accounts, thereby relaxing existing budget constraints and raising the demand for suppression and encouraging more frequent adoption of a full suppression response. Whether or not this policy change served to increase or decrease the probability of adopting a full suppression response is investigated using an unpaired two-sample t-test with equal variances (H.2):

$$H_0: \Delta = 0,$$
$$H_1: \Delta \neq 0,$$
$$H_2: \Delta > 0,$$
$$H_3: \Delta < 0. \tag{H.2}$$

Here, the coefficient $\Delta = \Pr(s_i = 1 | flame_i = 1) - \Pr(s_i = 1 | flame_i = 0)$. The test statistic for (H.2) is distributed *t* with (N$-$2) degrees of freedom. If the assumption of a normal distribution of probabilities across each period is not satisfied, a non-parametric two-sample Wilcoxon rank-sum test can be conducted, which does not rely on the assumption of a normal distribution in the pre- or post-policy probabilities or an assumption of equal variances of probabilities across periods. A rejection of the null hypothesis in test (H.2) in favor of either of the one-sided alternatives would suggest that the true probability of adopting a full suppression response was significantly larger (H_2) or smaller (H_3) following the budget intervention in fiscal year 2010. If there is evidence that the true difference in probabilities is positive, it would suggest that the Flame Act policy intervention had a positive impact on the probability of adopting a full suppression response. This would support the theory that the FLAME Act reserve funds led to a greater probability of engaging in full suppression strategies in lieu of confinement, point protection, or monitoring strategies. However, it may also support the idea that efforts to engage in “let-burn” policies as laid out in the guidance for implementation of the Flame Act and were ineffective at achieving this goal. If instead there is evidence that the true difference in probabilities is negative, we would conclude that measures taken to encourage less aggressive suppression response following the FLAME Act were effective at decreasing the probability of adopting a full suppression strategy.

Finally, we can estimate a specification which can accommodate unobserved manager heterogeneity in the choice model specification. The pooled probability models (3.3-3.7) do not account for the influence of characteristics specific to incident manager, which are unobserved in a sample of ICS-209 reports containing manager suppression choices. We can apply a linear panel data specification to estimate the average partial effects on suppression probability of the various factors that drive manager choice behavior (Cameron and Trivedi, 2005):

$$\begin{aligned}\tilde{s}_{jt} = \alpha_0 + \alpha_1 \ln wuidist_{jt} + \alpha_2 complex_{jt} + \alpha_3 federal_{jt} + \alpha_4 human_{jt} + \alpha_5 highprep_t + \alpha_6 OR_{jt} \\ + \alpha_7 WA_{jt} + \gamma_0 flame_{jt} + \gamma_1 \ln wuidist_{jt} * flame_{jt} + \gamma_2 complex_{jt} * flame_{jt} \\ + \gamma_3 federal_{jt} * flame_{jt} + \gamma_4 human_{jt} * flame_{jt} + \gamma_5 highprep_t * flame_{jt} + \gamma_6 OR_{jt} \\ * flame_{jt} + \gamma_7 WA_{jt} * flame_{jt} + \mathbf{w}'_{jt}\boldsymbol{\beta} + u_j + \varepsilon_{jt}\end{aligned} \tag{3.8}$$

In equation (3.8), ε_{jt} is a random disturbance term with a mean of zero while u_j represents the unobserved factors specific to an incident manger. These characteristics are assumed to be constant and unique to an incident manager (justifying the application of a fixed effects (FE) estimator) or are instead assumed to be randomly distributed across the population of incident managers (justifying the use of a random effects (RE) estimator), (Wooldridge, 2020). As with the pooled model specification, estimation of equation (3.8) with panel data enables a Chow test for structural change (H.1).

To accommodate a similar test to (H.2) which controls for manager-level heterogeneity in the panel data structure, we can apply an FE logit model. However, there is a well-known incidental parameters problem associated with the FE logit estimator, leading to inconsistency of the estimated parameters (Greene, 2018). This issue prohibits the application of a fixed-effects or “within” transformation of model variables, since the manager-level unobservable are not removed when estimating a nonlinear model. However, we can instead apply the Correlated Random Effects (CRE) logit model, which uses the Mundlak (1978) transformations of the model variables to approximate the FE logit estimators M(Greene, 2018). The CRE logit model is written as:

$$
\begin{aligned}
\Pr\left[\tilde{s}_i = 1 \middle| \mathbf{x}_{jt}, \mathbf{w}_{jt}\right] \\
&= \Lambda(\alpha_0 + \alpha_1 \ln wuidist_{jt} + \alpha_2 complex_{jt} + \alpha_3 federal_{jt} + \alpha_4 human_{jt} \\
&+ \alpha_5 highprep_t + \alpha_6 OR_{jt} + \alpha_7 WA_{jt} + \gamma_0 flame_{jt} + \gamma_1 \ln wuidist_{jt} * flame_{jt} \\
&+ \gamma_2 complex_{jt} * flame_{jt} + \gamma_3 federal_{jt} * flame_{jt} + \gamma_4 human_{jt} * flame_{jt} \\
&+ \gamma_5 highprep_t * flame_{jt} + \gamma_6 OR_{jt} * flame_{jt} + \gamma_7 WA_{jt} * flame_{jt} + \mathbf{w}'_{jt}\boldsymbol{\beta} + \bar{\mathbf{x}}_j \boldsymbol{\delta}_1 \\
&+ \bar{\boldsymbol{w}}_j \boldsymbol{\delta}_2 + u_j)
\end{aligned} \tag{3.9}
$$

Here, the variables represented by the matrices in $\bar{\mathbf{x}}_j$ and $\bar{\boldsymbol{w}}_j$ are the group means of the socioeconomic factors and weather or climate factors, respectively. Equation (3.9) is estimated using maximum-likelihood with an adaptive Gauss-Hermite quadrature integration method (Naylor and Smith, 1982).

4.3. Data

The dataset used for estimation of the pooled models (3.3-3.7) consists of 16,065 reports filed by incident managers overseeing fires in Oregon, Washington, and California from June of 2005 to December of 2013. Around 70 percent of the reports were filed in California, 20 percent in Oregon, and the remaining 10 percent were filed in Washington. Suppression strategies are chosen by incident managers and these choices are recorded through publicly available ICS-209 incident management forms. The data shows that 90.1 percent of managers in the sample never choose an alternative to a "full suppression" strategy across any of the reports they filed over this period. Each ICS-209 form contains information about the daily weather information ($temp_i, windspeed_i, relhum_i$) on the date of the chosen suppression strategy. Many reports have missing information on this daily weather (see Table A.1). When considered in a model with other missing data ($wuidist_i$), the estimation sample drops considerably to where perfect prediction is determined by some variables within the remaining observations. As discussed below, a larger estimation sample can be obtained by using monthly climate data available from the PRISM Climate Group (PRISM, 2020).

The ICS-209 forms have been geo-referenced to each incident's ignition point using the spatial Fire Occurrence Data (FOD) for the United States (Short, 2018). This allows each report filed by an incident manager to be linked to surrounding environmental or geographic characteristics of the decision environment that are not already recorded in the ICS-209 forms (such as the value of surrounding residential properties and the distance of each fire's ignition point to the nearest zone designated as "wildland-urban interface"). Figure 4.3 shows a map of all 1,231 fire ignition locations across California, Oregon, and Washington from June 2005 to

December 2013. Table A.1 provides a description of each variable in the merged cross-sectional dataset, its source, and its summary statistics.[34]

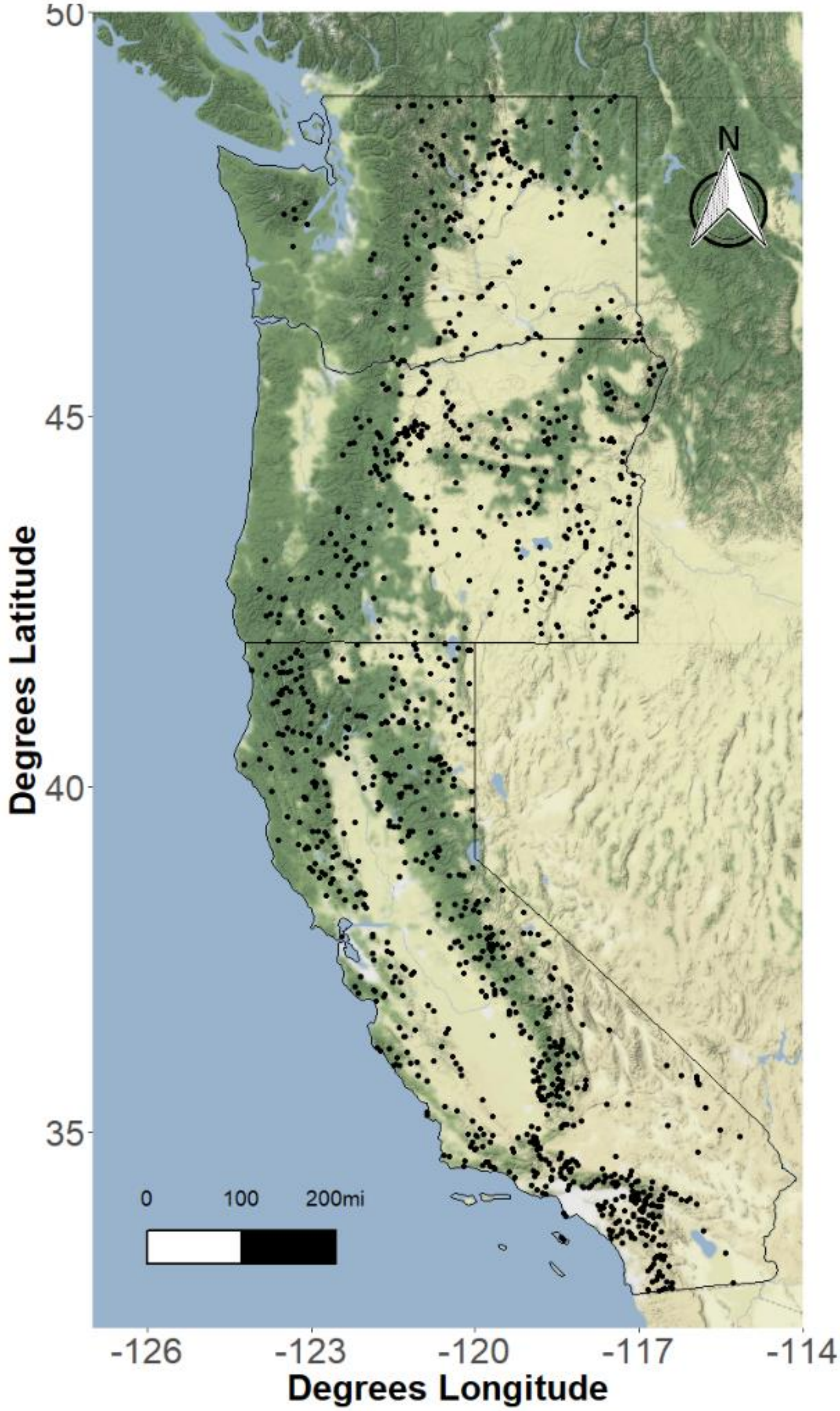
The data is cleaned and organized in four steps as follows.[35] First, the incident management data from each suppression incident across all U.S. states is cleaned and prepared for linkage with other dataframes. The incident management dataframe contains information about the chosen suppression strategy (s_i), the date (t) which the report was filed, the day's weather information ($temp_i, windspeed_i, relhum_i$), the location of the incident's ignition (if known), and the cause of the fire incident, if known ($human_i$). Second, the distances from each fire's ignition point are recorded and linked to the latitude and longitude coordinates listed in each ICS-209 report and a spatial data layer indicating zones of the "wildland-urban interface" (WUI) are also obtained (Radeloff et al., 2017; Martinuzzi et al., 2015). Distances from each ignition point (in thousands of meters) to the nearest WUI zone are calculated and then merged with the estimation dataframe ($wuidist_i$). Third, a time series dataset providing information about the National Preparedness Level is obtained from the National Interagency Fire Center (NIFC) and linked to each of the reports listed in the estimation dataframe based on the date of the filed report (PL_i^h). Finally, the ignition locations and dates are exported into a series of files that are used to obtain monthly climate data from the PRISM climate group (PRISM, 2020). The downloaded climate data files are then merged with the estimation dataset, providing information on average temperature ($mtemp_i$), precipitation ($mprecip_i$), minimum vapor pressure deficit

[34] A panel dataset can be aggregated using the daily decisions of managers in the dataset. An empirical application using this aggregated panel data is presented in Appendix B and the summary data used for these models is presented in Table B.1.
[35] See supplementary material for the Stata script used for cleaning and linking datasets. Data and script files are available from the author upon request.

($mminvpd_i$), and maximum vapor pressure deficit ($mmaxvpd_i$) in the month when the fire's ignition occurs.

In the pre-FLAME time period, 8.2% of ICS-209 forms reported a fire-use strategy, while 10.5% of forms reported a strategy other than full suppression in the post-FLAME time period. Around 72% of all reports were managed by federal agencies, and the remaining 29% by state agencies (this percentage is fell to around 70% in the post-FLAME time period). We also note that 31% of reports filed during the sample period occurred on days of high national preparedness. In both the pre- and post-FLAME periods, 31% of reports were managed during days with a high national preparedness level. Overall, 57% of reports were managed by Type 1 or Type 2 incident management teams, but this percentage fell from 62% in the pre-FLAME period to 47% in the post-FLAME period. Ignitions known to be human-caused at the time of the filed report consisted of 13% of all reports filed, and this percentage was approximately equal across the pre- and post-FLAME periods. Consistent with the results presented by Cullen et al. (2020), our dataset finds a strong and statistically significant correlation between the national preparedness level ($highprep_i$) and human-caused ignitions ($human_i$) ($\chi^2_{df=1} = 105.92^{***}$). Similarly, we find a strong and statistically significant correlation between incident complexity ($complexity_i$) and the preparedness level ($\chi^2_{df=1} = 494.50^{***}$). Therefore, omission of either $highprep_i$ or $complexity_i$ in a model seeking to estimate the effect of $human_i$ can lead to finite-sample bias or inconsistency of the estimated parameters. We include all 3 covariates in each specification of the probability equation (3.2) alongside the other socioeconomic factors $federal_i$ and $\ln wuidist_i$.

Figure 4.3 -Map of Wildfire Ignition Points in California, Oregon and Washington (June 2005-December 2013)



4.3.1. Manager-level panel data

Using the date of the filed ICS-209 report as the time variable (t) and a unique identifier for each incident commander managing the fire event (j) can enable the panel data structure needed to estimate equation (3.8). The resulting unbalanced panel data enables the estimation of a suite of models that allows for unobserved variation unique to each incident commander to be controlled for in a regression model of suppression strategy choices. While an unbalanced panel dataset can be constructed from the pooled data in order to control for unobserved heterogeneity of each incident manager, caution should be used with before use of this aggregated information. The unbalanced panel can be constructed based on daily time-varying information (t) and cross-sectional information (j). However, there are many instances in the dataset where a manager files more than one report on a single day (sometimes updating the chosen suppression strategy for that day or the daily weather variables). In these cases, a judgement must be made about which report to drop if daily-varying time information is needed to fit the manager-day panel data structure. Additionally, there is considerable judgement on behalf of the analyst about the correct link between reports filed by the same incident commander in cases where the incident commander does not consistently report their full name on each ICS-209 form. Managers often oversee more than one fire incident, sometimes in different regions and sometimes implementing different suppression strategies. However, their name is often not reported consistently across these incident reports. For these reasons, the set of reports included in the panel dataset (Appendix B) are a subset of the reports available in the pooled dataset (Appendix A).

An attempt was made to overcome these issues to construct an unbalanced panel dataset with 1,658 days and 2,478 different incident commanders. Managers in the sample frame file 4.7 reports on average, but some managers file as many as 126 reports. The data used to estimate panel data choice models are summarized in Appendix B, Table B.1. Some incident commanders only file reports over a few of these days, while others may file several hundred reports across these days. In either case, there is considerable propensity for managers to "drop out" of the sample, and "drop back in." The propensity to "drop in and out" of the sample is likely a characteristic that is unique to an incident manager but unobserved (such as their experience, ability, risk tolerance, career choices, or reservation wage). This assumption supports the use of a fixed-effects estimator on the unbalanced panel since it allows for unobserved manager-specific factors to be correlated with the observable covariates, without sacrificing the efficiency of the remaining estimated parameters. If the reason for dropping in and out of the sample is unique to each incident manager and related to the included covariates in equations (3.3-3.9), it would prohibit the use of a random effects estimator with this data, since the random effects estimator assumes that $cov(u_j, \mathbf{x}_{jt}) = 0$ (Wooldridge, 2020). It is unlikely for manager-specific unobservable characteristics to be unrelated with time-varying factors of interest that are included in the model (e.g. $complex_{jt}, federeal_{jt}$). This is because federally-employed incident managers work under a different wage rate than non-federally contracted managers and managers of high complexity fire crews have different skills or managerial experience. Therefore, we expect a fixed effects estimator to provide a more consistent estimation of average partial effects, since these manager-specific unobserved factors are removed under the fixed effects transformation. However, a Hausmann test may indicate if there is a sufficient deviation between the fixed- and random-effects coefficients, rendering statistical support for the fixed-effects specification if the null hypothesis of the test is rejected. To account for correlation of estimated residuals across managers, inferences made with the coefficients can be conducted using standard errors clustered at the manager level. However, inference should be made with caution as considerable within-group correlation remains from persistence in choices (managers are likely to continue to adopt the strategy the selected on the previous day).

4.4. Results

The use of daily weather control variables ($temp_i, windspeed_i, relhum_i$) in addition to the monthly climate controls ($mtemp_i, mprecip_i, mminvpd_i, mmaxvpd_i$) in the specification of equation (3.2) is problematic due to missing data and a reduction in the estimation sample. A restricted model which includes only the monthly climate variables yields a larger estimation set (N=15,577), compared to an unrestricted model where daily weather variables are also included (N=11,662). As with the pooled data models, the panel models are estimated with missing observations (N=8,251) due primarily to missing weather information in the ICS-209 forms. Panel data choice models estimated without the daily weather controls provides a larger estimation set (N=11,610).

We summarize the preferred model for each of the specifications in Table 4.2 (unrestricted pooled data model, restricted pooled data model, unrestricted linear panel data model, and restricted linear panel data model). We refer to these models when interpreting our results but refer readers to Appendices A and B for further model comparisons and hypothesis tests used to narrow our focus on the set of models presented in Table 4.2.

Table 4.2 – Estimated Marginal Effects from Binary Choice Models+++

	Pooled Data Models		**Panel Data Model**	
Dep. Variable:	s_i	s_i	s_{jt}	s_{jt}
Coefficient	Logit (unrestricted)	Complementary log-log (restricted)	CRE Logit (unrestricted)	CRE Logit (restricted)
Intercept	-	-	-	-
$\ln mtemp_{jt}$	-0.41***	-0.01	0.11	0.24*
	(0.06)	(0.06)	(0.15)	(0.10)
$\ln mprecip_{jt}$	0.03**	0.02*	0.03**	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
$\ln mminvpd_{jt}$	0.03*	0.02	0.00	-0.03*
	(0.01)	(0.01)	(0.02)	(0.01)
$\ln mmaxvpd_{jt}$	0.14***	0.01	0.11**	-0.02
	(0.02)	(0.02)	(0.04)	(0.03)
$\ln dtemp_{jt}$	0.03*	-	0.01	-
	(0.01)		(0.01)	
$\ln windspeed_{jt}$	0.01	-	0.00	-
	(0.00)		(0.02)	
$\ln relhum_{jt}$	0.02**	-	0.00	-
	(0.01)		(0.01)	
$\ln elev_{jt}$	-0.24***	-0.18***	-0.09***	-0.06**
	(0.02)	(0.01)	(0.03)	(0.02)
$\ln wuidist_{jt}$	-0.04***	-0.03***	-0.03**	-0.01
	(0.01)	(<0.01)	(0.01)	(0.01)
$human_{jt}$	0.04***	0.04***	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
$complex_{jt}$	0.05***	0.05***	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
$federal_{jt}$	-0.08***	-0.06***	-0.07***	-0.08***
	(0.02)	(0.01)	(0.02)	(0.02)
$highprep_t$	0.10***	0.08***	0.06***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
OR_{jt}	0.01	0.03***	-0.02	-0.02
	(0.01)	(0.01)	(0.02)	(0.01)
WA_{jt}	-0.03**	-0.05***	0.00	-0.03
	(0.01)	(0.01)	(0.01)	(0.02)
$flame_{jt}$	0.35***	1.29***	-0.85	0.35***
	(0.02)	(0.28)	(0.63)	(<0.01)
$flame_{jt} * \ln mtemp_{jt}$	-0.17	-0.59***	-0.54*	-0.58***
	(0.10)	(0.09)	(0.21)	(0.17)
$flame_{jt} * \ln precip_{jt}$	0.02	0.02*	-0.02	0.00

	(0.01)	(0.01)	(0.02)	(0.01)
$flame_{jt} * \ln mminvpd_{jt}$	0.05**	0.06***	0.08**	0.07***
	(0.02)	(0.01)	(0.03)	(0.02)
$flame_{jt} * \ln mmaxvpd_{jt}$	0.12**	0.26***	0.15**	0.21***
	(0.04)	(0.03)	(0.05)	(0.04)
$flame_{jt} * \ln dtemp_{jt}$	-0.12***	-	-0.02	-
	(0.03)		(0.02)	
$flame_{jt} * \ln windspeed_{jt}$	0.01	-	0.00	-
	(0.01)		(0.01)	
$flame_{jt} * \ln relhum_{jt}$	-0.03**	-	0.01	-
	(0.01)		(0.01)	
$flame_{jt} * \ln elev_{jt}$	0.15***	0.10***	-0.06	0.06*
	(0.02)	(0.02)	(0.04)	(0.03)
$flame_{jt} * \ln wuidist_{jt}$	0.04***	0.02***	0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
$flame_{jt} * human_{jt}$	-0.03	-0.06**	0.05***	0.04*
	(0.02)	(0.01)	(0.02)	(0.02)
$flame_{jt} * complex_{jt}$	0.01	0.01	0.03*	0.04**
	(0.01)	(0.01)	(0.01)	(0.02)
$flame_{jt} * federal_{jt}$	0.06	0.02	0.02	-0.01
	(0.05)	(0.02)	(0.04)	(0.04)
$flame_{jt} * highprep_{t}$	-0.15***	-0.09***	-0.08***	-0.04**
	(0.02)	(0.01)	(0.02)	(0.01)
$flame_{jt} * OR_{jt}$	-0.05**	-0.08***	-0.02	-0.04
	(0.02)	(0.01)	(0.02)	(0.02)
$flame_{jt} * WA_{jt}$	0.05***	0.06***	0.02	0.03
	(0.01)	(0.01)	(0.03)	(0.02)
Chow test for structural change across time (H.1)	$\chi^2_{15} =$ 299.74***	$\chi^2_{12} =$ 385.67***	$\chi^2(12) =$ 52.94***	$\chi^2_{12} =$ 90.64***
Unpaired two-sample t-test of total effect of policy change (H.2)	$\hat{\Delta}$=-0.02 $t^*(11660) =$ -5.82***	$\hat{\Delta}$=-0.02 $t^*(15575) =$ -10.36***	$\hat{\Delta}$=-0.03 $t^*(8249) =$ -15.17***	$\hat{\Delta}$=-0.04 $t^*(11608) =$ -19.88***
Two-sample Wilcoxon Rank-sum test (H.2)	$z^* =$ 35.14***	$z^* =$ 30.55***	$z^* =$ 13.94***	$z^* =$ 18.99***
Log-Lik.	LL(32)= -1831.05	LL(26)= -2892.68	LL(64)= -683.78	LL(52)= -1110.85
Obs.	11,662	15,577	8,251	11,610

**p<0.05; **p<0.01; ***p<0.001*

+++ Marginal effects for continuous covariates are calculated as Average Partial Effects (APE): $N^{-1}\sum_i g\left(\hat{\alpha}_0 + \mathbf{x}_i'\hat{\boldsymbol{\alpha}} + \mathbf{z}_i{}'\hat{\boldsymbol{\gamma}} + \mathbf{w}_i'\hat{\boldsymbol{\beta}}\right)\hat{\alpha}_j$. Marginal effects for the j^{th} binary covariate represent the average difference in probabilities from a change in the binary indicator: $N^{-1}\sum_i\left\{G\left(\hat{\alpha}_0 + \hat{\alpha}_j\left(x_j = 1\right) + \mathbf{x}_i'\hat{\boldsymbol{\alpha}} + \mathbf{z}_i{}'\hat{\boldsymbol{\gamma}} + \mathbf{w}_i'\hat{\boldsymbol{\beta}}\right) - G\left(\hat{\alpha}_0 + \hat{\alpha}_j\left(x_j = 0\right) + \mathbf{x}_i'\hat{\boldsymbol{\alpha}} + \mathbf{z}_i{}'\hat{\boldsymbol{\gamma}} + \mathbf{w}_i'\hat{\boldsymbol{\beta}}\right)\right\}$.

4.4.1. Pooled data model results

The estimated skewed probit model (3.5) finds no evidence of an asymmetric probability distribution when the daily weather controls are included ($\hat{\delta} = 0$) but finds evidence of an asymmetric probability distribution when they are omitted ($\hat{\delta} = 2.36$). Therefore, the estimated average partial effects displayed in Table 4.2 are best estimated by a probit or logit model if the unrestricted specification is preferred but are better approximated by a complementary log-log model if the restricted specification is preferred. In either case, the average marginal effects of the LPM (presented in Appendix A, Tables A.2 and A.3) are similar to the partial effects obtained using the nonlinear probability models.

A test of the joint significance of interactions with the $flame_i$ variable (hypothesis (H.1)) provides evidence to support the alternative hypothesis (H_A) of a structural break after the implementation of the Flame Act in fiscal year 2010. That is, we find evidence to support the existence of a change in the slope parameters describing the data-generating process across pre- and post-FLAME Act time periods. We also reject the null hypothesis of (H.2) using predicted probabilities from both the unrestricted logit model, and again from the restricted complementary log-log model. From these tests, we conclude that there is evidence that the FLAME Act's implementation, beginning in 2010, had a negative impact on the expected probability that a manager selected a full suppression response.

We conduct a simple placebo test on both the restricted and unrestricted models and find that after re-defining the post-policy period as FY2009 to FY2014, we still find an effect of the intervention on the expected choice probability (reject the null of hypothesis (H.2)).[36] However, we do find evidence to reject the null hypothesis of (H.1) under this definition of the post-policy time period,[37] indicating that there was a structural change following the 2009 policy guidance. The placebo policy intervention had a similar effect on the probability of adopting full suppression as did the FLAME Act intervention. This seems to disagree with the results presented by Young et al. (2020), who also assume the existence of a policy intervention following the release of the February 2009 fire policy guidance and find limited to no effect of the 2009 policy guidance on fire size or duration. However, Young et al (2020) do not conduct a placebo test to determine if the implementation of the FLAME Act had a similar impact on fire management outcomes about a year after the 2009 policy guidance was released. Changing the assumed timing of the structural break to the post-FLAME Act period (FY2010 to FY2014) provides a more complete picture of the effect of the combined fire policy intervention during occurring during the 2009-2010 period. While the 2009 fire policy guidance *and* the FLAME Act had a significant impact on the expected probability of choosing a full suppression response, rendering identification of the FLAME Act's effect inconclusive, these two policies altered the suppression environment such that socioeconomic factors and weather factors played different roles after their implementation.

For example, we learn from the $flame_i$ interaction terms about the nature of this structural change in the FY2010 to FY2014 time period. For example, the estimated unrestricted regression model estimates that a 10 percent increase in an incident's distance from the WUI will

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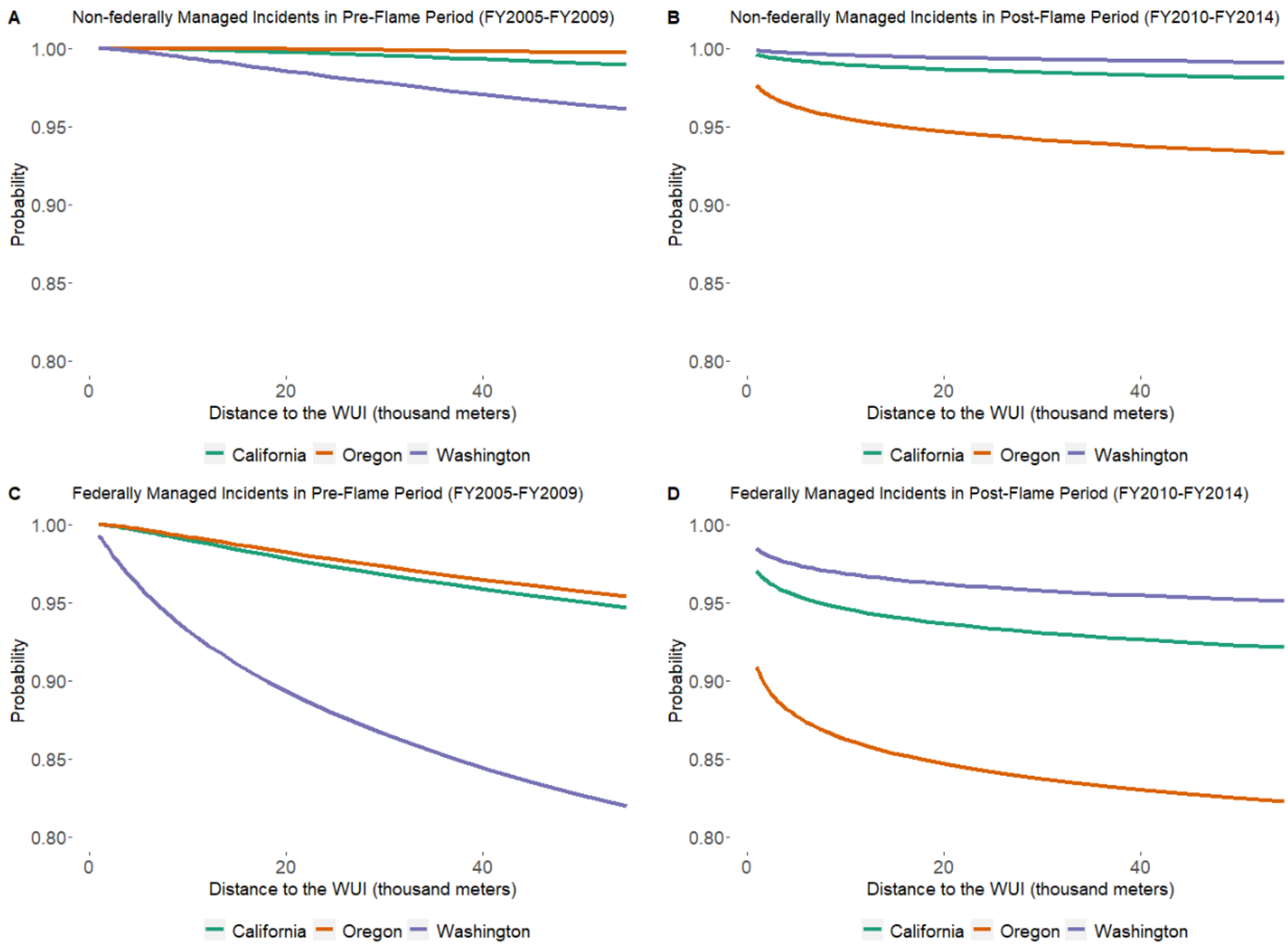
[36] Application of the restricted complementary log-log model yields a test statistic of z^*=45.52***, while the unrestricted logit model estimates a z^*=47.52***. These results indicate a rejection of the null hypothesis of (H.2). Both of these tests suggest that the expected difference in suppression probabilities before and after the 2009 policy guidance was statistically distinguishable from 0.

[37]The estimated test statistic for (H.1) under the placebo definition of the policy intervention is: $\chi^2_{12} = 305.40^{***}$.

decrease the probability of suppression by 0.3 probability points, on average. This supports the hypothesis that incident managers are less likely to suppress fires burning at greater distances from high-valued assets in the WUI, but are more likely to engage in full suppression on fires burning closer to residential values at risk, and so may be averse to downside risks (Rossi and Kuusela, 2020). However, following the passage of Flame Act, this effect is reduced: a 10 percent increase in an incident's distance from the WUI will decrease the probability of suppression by 0.1 probability points. With the budget interventions introduced by the Flame Act, managers were still less willing to suppress fires when they burn farther from the WUI, however the availability of the reserve funds may have reduced their willingness to do so. In other words, larger distances from the WUI were not as meaningful in lowering the probability of adopting full suppression as they were in the pre-FLAME period.

These effects are evident in Figure 4.4, which uses the predictions from the estimated restricted model in Table 4.2 to show the relationship between the predicted probability of adopting a full suppression response and the incident's distance from the WUI for each of the three states included in the sample. Notably, states were affected differently by the Flame Act. Relative to California, Oregon experienced a greater probability of adopting full suppression prior to the policy change but experienced a lower probability of adopting full suppression after the policy change. We also see in Figure 4.4 that California was relatively sensitive to a change in distance from the WUI during the pre-FLAME years, meaning that greater percentage increases in distance had a larger effect on the probability of adopting a full suppression response. However, this sensitivity fell dramatically at larger distances following the implementation of the FLAME Act.

Figure 4.4 - Effects of an Incident's Distance to the WUI on the probability of adopting a Full Suppression response before and after the implementation of the Flame Act



This estimated relationship is further broken up into federally- and non-federally managed incidents (as illustrated in Figure 4.4 by the difference between panels A and B vs. panels C and D) and across the pre- and post-Flame Act time periods (panels A and C vs. panels B and D). Overall we estimate that relative to state-managed incidents, the probability of adopting a full suppression response on federally managed incidents is 0.08 probability points lower, on average. This effect of federally managed incidents was no lower following the implementation of the FLAME Act. This result illustrates the difference in approaches to fire management policy across federal and state land management agencies, but suggests the FLAME Act was ineffective at encouraging fewer full suppression responses.

However, the model estimates that both federal and non-federal agencies were less sensitive to changes in an incident's distance from the WUI following the change in policy. This influenced some states' capacity to let fires burn when incidents occurred at greater distances from the WUI. Specifically, we estimate that following the policy change, Washington experienced a relatively lower probability of a manager adopting a full suppression response when incidents occurred relatively closer to the WUI (within about 7,389 meters for state managed incidents and within 3,004 meters for federally managed incidents), but they experienced a relatively higher probability of adopting a full suppression response when incidents occurred farther from the WUI (at distances greater than 7,389 meters for state managed incidents and at distances greater than 3,004 meters for federally managed incidents). In contrast, incident managers in Oregon were less likely to adopt a full suppression response on both state and federally managed incidents following the policy change. On average, the FLAME Act had no effect on the probability of choosing a full suppression response (H.2), but we see that this total effect from the policy varies across states and over an incident's distance from the WUI. The policy was most effective at lowering the probability of a manager adopting a full suppression response when incidents burn in and around the WUI, but the policy may have encouraged greater reliance of full suppression strategies at distances farther from the WUI in some regions.

We find evidence that under our definition of incident complexity, a higher complexity can lead to an increase in full suppression adoption. Incidents classified as Type 1 or Type 2 incident complexity (which are managed by Type 1 or 2 incident managers) increase the probability of adopting a full suppression approach by an estimated 0.05 probability points.

However, the FLAME Act had no effect on incident complexity's capacity to increase the probability of adopting a full suppression response.

We also find some evidence that other institutional factors are important determinants for explaining suppression choices. The pooled data models estimate that a manager's knowledge that an incident is human-caused will increase the probability that managers choose to adopt a full suppression strategy by 0.04 probability points, on average (as estimated by both the restricted and unrestricted models). The unrestricted logit model finds no evidence that the FLAME Act had any effect on a human-caused fire's capacity to induce more frequent adoption of a full suppression response. However, the restricted model estimates that following the FLAME Act, human-caused ignitions had no effect on a manager's likelihood to choose a full suppression strategy.

However, we find strong effects of the national preparedness level in both the pre- and post-Flame time periods. The models estimate that the probability of selecting a full suppression strategy increases during times of high-resource demand as measured by the national preparedness level (after controlling for climate and weather factors that may correlate strongly with preparedness level). The restricted complementary log-log model (Table 4.2) finds that if the national preparedness level is 4 or 5 (indicating high preparedness and strong demand for suppression resources), the probability of adopting a full suppression response increases by 0.10 points. However, following the FLAME Act, this effect falls to 0.02 points. The unrestricted logit model (Table 4.2) estimates a similar effect (an increase of 0.10 points in the pre-Flame period and a much smaller effect of 0.02 points in the post-Flame period). This result suggests that the Flame Act may have been able to smooth-out resource demand across jurisdictions through improved allocation and resource sharing, as individual managers became less likely to adopt a full suppression response following the FLAME Act when resources were in high demand elsewhere in the country.

Monthly climate data was also an important determinant of the probability of selecting a full suppression strategy over the sample period. A 10 percent increase in the monthly minimum vapor pressure deficit, increased suppression probability by between 0.3 points, on average, while a 10 percent increase in the monthly maximum vapor pressure deficit increased suppression probability by between 1.4 points. However, following the FLAME Act a 10 percent increase in monthly maximum vapor pressure deficit increased suppression probability by 2.6 points. This supports the intuitive claim that the probability of adopting full suppression was larger under drier conditions. The unrestricted logit model (Table 4.2) estimates that a 10 percent increase in monthly temperature decreased suppression probability by 4.1 points, on average. The restricted logit model (Table 4.2) estimates a slightly larger effect of 3.7 points. Both models estimate that this effect increased to 5.9 probability points following the FLAME Act's implementation, although this post-policy effect is only significant under the restricted model specification. The overall negative effect of monthly temperature may be explained by an incident manager's increased willingness to let fires burn to avoid heat-exhaustion or injury to firefighters under high-temperature conditions, and instead focus more on full suppression when conditions ae cooler. The pooled models in Table 4.2 estimate that a 10 percent increase in monthly precipitation increased suppression probability by 0.3 probability points (unrestricted model) or 0.2 probability points (restricted model). This further supports the idea that managers had a tendency to focus on suppression when conditions were more favorable (wetter) and focus on other management operations like evacuations when precipitation conditions were less conducive (drier) for carrying out aggressive suppression operations.

The unrestricted logit model includes daily weather controls ($dtemp_i, windspeed_i$, $relhum_i$). The model estimates that daily temperature and the relative humidity measure taken during the time of the filed reports increased the probability of suppression in the pre-FLAME period, but decreased the probability of suppression in the post-FLAME period. Additionally, we find joint significance of the daily weather controls, indicating that when considered together, daily temperature, windspeed, and the day's relative humidity measure can significantly impact a manager's suppression decision.

4.4.2. Panel data model results

We reject the null hypothesis of a Breusch-Pagan Lagrange Multiplier test, indicating that individual-level random effects are significant under the assumption of a linear specification for equation (3.2). Therefore, the RE estimator provides a significant improvement over OLS in terms of its ability to control for manager-specific factors. However, based on the Hausman test, the estimated coefficients of the FE specification are statistically different from those of the RE specification. This agrees with the rejection of the null hypothesis from a test of the joint significance of Mundlak terms included as part of the CRE logit estimator (in both the restricted and unrestricted specifications). Therefore, we conclude that the FE estimator is preferred for analyzing magnitude of average partial effects of model variables, although we caution against using the FE estimator to draw statistical inference since the model suffers from heteroskedasticity. In what follows, we use the partial effects calculated using the CRE logit estimator (presented in Table 4.2).

The CRE logit estimator finds strong evidence of a structural break following the FLAME Act, but there is also an estimated difference of a structural break under the placebo intervention period (FY2009 to FY2014).[38] This rejection of the null hypothesis in (H.1) agrees with the results from the pooled models. However, the nonlinear panel data model rejects the null hypothesis in (H.2) and finds evidence to support alternative hypothesis H_3, under both the initial treatment period (FY2010-FY2014) and the placebo treatment period (FY2009-FY2014).[39] This suggests that either the FLAME Act served to decrease the probability of adopting a full suppression response, or that the 2009 policy guidance *was* effective at encouraging let-burn strategies and this outweighed any positive effects introduced by the accessibility of reserve funds available under the FLAME Act beginning in FY2010.

The unrestricted CRE logit estimator finds that a 10 percent increase in a fire's distance from the WUI decreases the probability of choosing suppression by 0.3 probability points, on average. The restricted CRE logit estimator estimates that this effect is a reduction of 0.1 probability points but is significant at only the 6 percent level. This effect is slightly smaller than what was estimated from the pooled data models. In contrast to the pooled models, the CRE logit estimator finds limited evidence that the Flame Act intervention increased or decreased the effect of a fire's distance from the WUI. The panel models find that there is an increase in the size of the average effect of distance from the WUI in lowering the frequency of adoption of "let-burn" strategies occurring on state-managed incidents, although this effect is very small. However, there was a decrease in the capacity for distance from the WUI to lower the probability of adoption full suppression on federally managed fires following the Flame Act's implementation. The unrestricted model finds an estimated marginal effect of adopting full suppression that was 2

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[38] Using the restricted CRE logit model, the estimated test statistic for (H.1) under the placebo definition of the policy intervention is: $\chi^2_{12} = 74.75^{***}$.

[39] Using the restricted CRE logit model, the estimated test statistic for the two-sample Wilcoxon rank sum test (H.2) under the placebo definition of the policy intervention is: $z^* = 34.45^{***}$. Using the unrestricted model, the test statistic is: $z^* = 27.02^{***}$.

percentage points lower for federally managed incidents relative to state managed incidents, on average, but following the FLAME Act this difference vanished. This can be seen in Table 4.3, where the average marginal effects of $\ln wuidist_{jt}$ as estimated by the unrestricted CRE logit model are listed for state- and federally-managed incidents in the pre- and post-FLAME periods. The policy change was effective at reducing the probability of full suppression on state-managed fires at increasing distances from the WUI but raised the probability of full suppression at larger distances from the WUI on federally-managed fires. These effects are very small in magnitude, potentially reflecting the counteracting effects of the 2009 policy guidance.

Table 4.3 - Average marginal effects of the natural logarithm of an incident's distance to the WUI on state and federally managed incidents in the pre- and post-FLAME Act time periods

Unrestricted Model (N=8,251)	Pre-FLAME years (FY2005-FY2009)	Post-FLAME years (FY2010-FY2014)
State-managed incidents	-0.00 (<0.01)	-0.01** (<0.01)
Federally-managed incidents	-0.02** (<0.01)	-0.01** (<0.01)

**p<0.05; **p<0.01; ***p<0.001*

As with the pooled data models, we also find evidence from the CRE logit estimator that other socioeconomic and institutional factors were important determinants for explaining variation in suppression choices. The estimated panel data models find that a manager's knowledge of an incident being human-caused ($human_{jt}$) did not significantly affect the probability that managers choose to adopt a full suppression strategy before the policy intervention, but it raised the probability of adopting full suppression by 4 to 5 percentage points following the intervention. The CRE logit estimator provides evidence that the national preparedness level ($highprep_t$) had a large positive and statistically significant impact on suppression choices in the pre-FLAME period, but the FLAME Act significantly lowered this effect. Individual managers were more likely to adopt a full suppression response during days with high resource demand prior to the FY2010 policy intervention, but this effect diminished to zero after the implementation of the FLAME Act. The magnitude and size of the effects of the national preparedness level are similar and consistent across the preferred pooled and panel data models. We also estimate that the probability of adopting full suppression is 4 percentage points higher, on average, for highly complex incidents ($complex_{jt}$) only during the post-FLAME Act period. This disagrees with the estimates from the pooled models which find a positive effect of incident complexity in the pre-FLAME period, but no effect of incident complexity in the post-FLAME period.

With regard to climate and weather factors in the panel data models, we estimate a similar magnitude and significance of the on the effects of drier conditions on the probability of choosing a suppression strategy in the post-FLAME period. The CRE logit specification using the manager-level panel finds a larger effect of the month's maximum vapor pressure deficit: a 10 percent increase in the monthly maximum vapor pressure deficit increases the probability of choosing suppression by 2.6 probability points, on average, in the post-FLAME time period (relative to a null effect in the pre-FLAME period). This result supports the claim that drier monthly conditions can significantly impact suppression choices, and that the percentage change in suppression probability from this effect is greater than that of social or institutional factors.

4.5. Discussion and conclusion

The estimated probability models in this paper find inconclusive evidence on the effects of the FLAME Act on the probability that managers choose to engage in full suppression of unplanned wildfires. While we find evidence that the FLAME Act implemented in Fiscal Year

2010 led to a reduction in the expected probability that an incident manager selects a full suppression response, we cannot distinguish this effect form the effect of an update to policy guidance released one year prior. The FLAME Act's implementation in Fiscal Year 2010 coincides with release of federal guidance of or wildfire policy during Fiscal Year 2009. Therefore, we may have detected a reduction in suppression probability due to the release of this guidance and this may have outweighed any positive impacts on suppression probability introduced by the accessibility of reserve funds available under the FLAME Act beginning in FY2010. The potential for counteracting effects may be why the reduction in suppression probability fell by only a small margin after fiscal year 2010. For this reason, evidence on the effects of reserve funding remains inconclusive. However, there is potential to expand the dataset and use a similar estimation framework to determine the effects of similar reserve funding mechanisms (such as those proposed under the Wildfire Disaster Funding Act) but which are not accompanied by an update to federal fire policy guidance.

However, we do find critical differences in this predicted probability across federal and non-federally managed wildfire incidents. The FLAME Act and the 2009 policy guidance encouraged federal land management agencies to embrace the restoration of fire regimes at the landscape scale via "let-burn" strategies like "point protection", "confinement", and "monitoring" of an ongoing fire when weather and climate conditions were appropriate. However, these same policies were not adopted by state forestry agencies. State fire protection programs such as those funded by the Oregon Department of Forestry and the California Department of Forestry and Fire Protection still overwhelmingly support an aggressive suppression response, and the FLAME Act did not successfully encourage adoption of "let-burn" strategies at the state level. The FLAME Act actually served to decrease the effects on a greater distance to human populations on the probability that federally managed incidents were managed under a full suppression response, but had the opposite effect on state-managed incidents.

Our results show that the FLAME Act did achieve its objective of decreasing the probability of full suppression, although this effect is indistinguishable from the effects of the 2009 fire policy guidance which was released around the same time. However, these effects were estimated to differ across states and distances of fires from the surrounding residential population. Other papers have found empirical evidence that a fire's proximity to residential values at risk can significantly impact suppression demand (Bayham and Yoder, 2020), but the estimated models in this paper are the first to show how this impact can differ across state and federally managed fires and under alternative budgetary institutions. Federally managed incidents across all three western states in our sample were less likely to be managed under a full suppression strategy following the FLAME Act's implementation. However, we estimate that this effect varied for fires managed closer to the wildland-urban interface. In Washington, fires were more likely to be managed under a full suppression strategy following the FLAME Act's implementation when fires burned close to the wildland-urban interface. However, they were more likely to be managed under full suppression following the FLAME Act's implementation when they burned farther from the wildland-urban interface. This perhaps reflects the effects of a change in the reserve funding mechanism, which may have encouraged less prudent use of annual suppression allocations on fires which were less threatening to surrounding populations. Only in Oregon did we estimate that the FLAME Act's implementation decreased the likelihood of full suppression adoption across all distances from the wildland-urban interface.

Our results also support those of Cullen et al. (2020) in that we find incident complexity to be a significant predictive factor affecting suppression choices under the probability models estimated using pooled data. While Cullen et al. (2020) find that Type 1 and Type 2 incidents are important factors for predicting the national preparedness level, we find that they can also be important predictors of the choice to implement a full suppression strategy. Our results also support the findings reported by Bayham and Yoder (2020) in that we estimate a positive and statistically significant impact of a high national preparedness level on an individual a manager's likelihood of adopting a full suppression response. This finding suggests that resource constraints, as measured by high national demand, can significantly impact suppression choices at the incident level. Specifically, we estimate that high national demand for suppression resources had the effect of raising an individual manager's likelihood of adopting a full suppression response, but that the FLAME Act intervention significantly reduced this probability such that, on average, the national preparedness level had no effect on choices following the intervention. This result on the effects of the national preparedness level is robust across all of the preferred specifications of the choice probability equation.

More importantly, we find strong and statistically significant effects of the monthly maximum vapor pressure deficit, indicating that drier conditions lead managers to more frequently adopt a full suppression response. We also find that landscape topography can be a key predictor of suppression response. Fires burning at high elevations are less likely to be managed under full suppression. These effects match our intuition about the effects of dryness and topography on suppression choices, but we find that these factors have a greater impact on suppression choices than many of our socioeconomic variables including the fire's distance to the wildland-urban interface.

Our statistical results do contain some important caveats that limit the interpretation of hypothesis (H.1), which finds evidence of a structural break in the marginal effects of socioeconomic, weather, and climatic factors following the implementation of the FLAME Act. It is important to distinguish between a manager's adoption of a full suppression strategy and their demand for suppression resources. While we may be tempted to conflate the adoption of a full suppression strategy with a greater demand for suppression resources, the estimated models in this paper do not suggest that more frequent adoption of a full suppression response necessarily implies a greater demand for suppression resources or larger expenditures on suppression effects. It may be that following the introduction of FLAME Act reserve funds, let-burn strategies became less resource-intensive despite the more frequent adoption of a full suppression response in some regions. While total suppression expenditures and the demand for air resources and ground crews may have increased following the availability of the FLAME reserve funds, the effect of the FLAME Act intervention on these variables is beyond the scope of this paper. This paper finds that these increases are coupled with a corresponding tendency to engage in full suppression responses to unplanned fire events, but we cannot draw inference on the effects of the FLAME Act reserve funds on resource demand or suppression expenditures. This question is left for future research.

To the extent that future research finds a greater demand for suppression resources alongside the adoption of a full suppression response, our model suggests that budgetary institutions can be a key factor that explains an increasing reliance in some regions on suppression effort relative to pre-fire risk mitigation or preparedness. Despite the increase in annual suppression appropriations under the new funding structure, the practice of off-budget financing for emergency suppression funding remains intact today (USFS, 2016). The development of a separate pool of funding, like the FLAME Act accounts or the new accounts set up under the Consolidated Appropriations Act, does not address the overutilization of suppression resources and may complicate fire management for some state agencies. The reason for this may be the incentive structure imposed by enabling incident managers and their overseeing agency to engage in fire suppression without full regard to the costs of their actions. The new funding structure may exacerbate the problem by creating new accounts earmarked specifically for suppression, while other land management appropriations are held constant. Essentially, the off-budget financing of emergency fire suppression effort and the availability of reserve funds serves to lower the effective marginal cost of suppression, thereby raising an incident manager's demand for suppression effort (Donovan and Brown, 2005; Lueck, 2012; Rossi and Kuusela, 2019).

One potential source of bias from the suite of models presented in this paper arises from measurement error. In all models, we defined the distance from where the suppression choice is implemented to the nearest WUI zone as the Euclidean distance between the fire's ignition point (where latitude and longitude information is available) and the nearest WUI zone. Fires often burn for weeks or months, spanning several thousand acres. Therefore, it is possible for this distance metric to be an inadequate proxy variable for the proximity between a WUI zone and the location where the manager's suppression strategy is implemented. Furthermore, the Euclidean distance between these two points does not capture the effect of any natural fire breaks that would render a close distance from the fire less threatening to residential values-at-risk (such as rivers or other non-burnable terrain).

Another source of measurement error relates to the assumption that values-at-risk of wildfire damage are solely residential. Our measure of value-at-risk is the distance of each incident's ignition to the nearest wildland-urban interface zone, as defined by a 2010 measurement of housing density (Radeloff et al., 2017). Typically, managers weigh the importance of residential values at risk against that of other ecosystem services, including sensitive wildlife habitat, timber resources, and watershed quality. Additional research may seek to estimate the probability models presented in this paper but instead redefine several of the model variables to better reflect the tradeoffs faced by incident managers.

Appendix A: Tables and Figures (Pooled Choice Data)

TABLE A.1 - DESCRIPTIVE STATISTICS FOR POOLED INCIDENT REPORT DATA

Variable	Description	Source	Mean (St. Dev.)	Min	Max	N
s_i	=1 if Full Suppression strategy, =0 otherwise	ICS-209	0.9085 (0.2883)	0	1	16,065
$wind_i$	Reported windspeed (mph)	ICS-209	10.1764 (19.4083)	0	1525	13,011
$dtemp_i$	Reported temperature (degrees F)	ICS-209	75.9956 (18.9782)	0	405.5	13,462
$relhum_i$	Reported relative humidity	ICS-209	31.1110 (19.6836)	0	721	12,372
$elev_i$	Elevation at ignition point (thousand ft.)	PRISM	3.6354 (1.9130)	0	9.6520	16,065
$mtemp_i$	Avg. temperature in month of ignition (degrees F)	PRISM	66.5566 (8.6518)	20.0	90.0	16,065
$mprecip_i$	Precipitation in month of ignition (inches)	PRISM	0.5336 (1.4719)	0	56.0	16,065
$mminvpd_i$	Minimum recorded vapor pressure deficit in month of ignition (hPa)	PRISM	5.4651 (2.9738)	0.1	20.32	16,065
$mmaxvpd_i$	Maximum recorded vapor pressure deficit in month of ignition (hPa)	PRISM	30.6122 (10.3509)	1.23	68.34	16,065
$wuidist_i$	Distance from ignition point to nearest wildland-urban interface zone (thousand meters)	SILVIS	5.7044 (6.1191)	0	47.74	15,577
$complex_i$	=1 if Type 1 or Type 2 incident complexity, =0 otherwise	ICS-209	0.5697 (0.4951)	0	1	16,065
$federal_i$	=1 if suppression response by federal agency, =0 otherwise	ICS-209	0.7173 (0.4503)	0	1	16,065
$flame_i$	=1 if report filed during or after FY2010 when FLAME reserve funds were available, =0 otherwise	ICS-209	0.3417 (0.4743)	0	1	16,065
FY_i	Fiscal Year during which the incident occurred.	ICS-209	2009 (2.5059)	2005	2014	16,065
$human_i$	=1 if ignition caused by human, =0 if by lightning or unknown cause	ICS-209	0.1297 (0.3360)	0	1	16,065
PL_i	National Wildfire Preparedness Level on day of reported ICS-209 form	NIFC	2.5850 (1.4045)	1	5	16,065

	(=1 for low preparedness, =5 for high preparedness)					
$highprep_i$	=1 if National Wildfire Preparedness Level on day of reported ICS-209 form is 4 or 5, =0 otherwise	NIFC	0.3106 (0.4628)	0	1	16,065
CA_i	=1 if incident occurs in California, =0 otherwise	ICS-209	0.6817 (0.4658)	0	1	16,065
OR_i	=1 if incident occurs in Oregon, =0 otherwise	ICS-209	0.1867 (0.3897)	0	1	16,065
WA_i	=1 if incident occurs in Washington, =0 otherwise	ICS-209	0.1012 (0.3015)	0	1	16,065

TABLE A.2 – Estimated Marginal Effects from Unrestricted Binary Choice Models with Pooled Incident Report Data+++

Dep. Variable:	$\boldsymbol{s_i}$	$\boldsymbol{s_i}$	$\boldsymbol{s_i}$	$\boldsymbol{s_i}$
Coefficient	LPM (robust s.e.)	Probit	Logit	Complementary Log-Log
Intercept	1.04***	-	-	-
	(0.25)			
$\ln mtemp_i$	-0.11	-0.34***	-0.41***	-0.20**
	(0.07)	(0.07)	(0.06)	(0.07)
$\ln mprecip_i$	0.05**	0.02*	0.03**	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
$\ln mminvpd_i$	0.03***	0.03*	0.03*	0.03*
	(0.01)	(0.01)	(0.01)	(0.01)
$\ln mmaxvpd_i$	0.07***	0.10***	0.14***	0.05*
	(0.01)	(0.02)	(0.02)	(0.02)
$\ln dtemp_i$	0.02	0.03*	0.03*	0.03*
	(0.02)	(0.01)	(0.01)	(0.01)
$\ln windspeed_i$	0.00	0.01	0.01	0.01
	(<0.01)	(<0.01)	(0.00)	(<0.01)
$\ln relhum_i$	0.02**	0.02***	0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
$\ln elev_i$	-0.11***	-0.21***	-0.24***	-0.17***
	(0.01)	(0.02)	(0.02)	(0.01)
$\ln wuidist_i$	-0.04***	-0.04***	-0.04***	-0.04***
	(<0.01)	(<0.01)	(0.01)	(<0.01)
$human_i$	0.06***	0.04***	0.04***	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
$complex_i$	0.05***	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
$federal_i$	-0.01*	-0.06***	-0.08***	-0.04***
	(<0.01)	(0.01)	(0.02)	(0.01)
$highprep_i$	0.06***	0.09***	0.10***	0.08***
	(<0.01)	(0.01)	(0.01)	(0.01)
OR_i	0.06***	0.02	0.01	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
WA_i	-0.03**	-0.03**	-0.03**	-0.04**
	(0.01)	(0.01)	(0.01)	(0.01)
$flame_i$	2.70***	0.36***	0.35***	0.36***
	(0.46)	(<0.01)	(0.02)	(<0.01)
$flame_i * \ln mtemp_i$	-0.84***	-0.30**	-0.17	-0.32**
	(0.15)	(0.10)	(0.10)	(0.11)
$flame_i * \ln precip_i$	0.01	0.02*	0.02	0.04***
	(0.02)	(0.01)	(0.01)	(0.01)
$flame_i * \ln mminvpd_i$	0.08***	0.05**	0.05**	0.05**
	(0.02)	(0.02)	(0.02)	(0.02)
$flame_i * \ln mmaxvpd_i$	0.34***	0.16***	0.12**	0.20***
	(0.04)	(0.04)	(0.04)	(0.03)

$flame_i * \ln dtemp_i$	-0.10*	-0.08**	-0.12***	-0.17***
	(0.05)	(0.03)	(0.03)	(0.03)
$flame_i * \ln windspeed_i$	0.03**	0.01	0.01	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
$flame_i * \ln relhum_i$	-0.03*	-0.03*	-0.03**	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
$flame_i * \ln elev_i$	0.02	0.12***	0.15***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)
$flame_i * \ln wuidist_i$	0.03***	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
$flame_i * human_i$	-0.02	-0.03	-0.03	-0.03
	(0.01)	(0.02)	(0.03)	(0.02)
$flame_i * complex_i$	0.02*	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
$flame_i * federal_i$	-0.04***	0.03	0.06	0.00
	(0.01)	(0.03)	(0.05)	(0.02)
$flame_i * highprep_i$	-0.04***	-0.13***	-0.15***	-0.10***
	(0.01)	(0.02)	(0.03)	(0.01)
$flame_i * OR_i$	-0.12***	-0.06***	-0.05**	-0.07***
	(0.02)	(0.01)	(0.01)	(0.01)
$flame_i * WA_i$	0.11***	0.05***	0.05***	0.07***
	(0.02)	(0.01)	(0.01)	(0.01)
Skewness coefficient from skewed probit model $(\hat{\delta})$	-	-0.03 (0.05)	-	-
Chow test for structural change across time (H.1)	$F^*(15,11630) =$ 19.95***	$\chi^2_{15} =$ 305.49***	$\chi^2_{15} =$ 299.74***	$\chi^2_{15} =$ 319.16***
Unpaired two-sample t-test of total effect of policy change (H.2)	-	$\hat{\Delta} = -0.02$ $t^*(11660) =$ -5.71***	$\hat{\Delta} = -0.02$ $t^*(11660) =$ -5.82***	$\hat{\Delta} = -0.02$ $t^*(11660) =$ -6.72***
Two-sample Wilcoxon Rank-sum test (H.2)	-	$z^* =$ 32.11***	$z^* =$ 35.14***	$z^* =$ 26.62***
R^2	0.173	-	-	-
R^2_a	0.170	-	-	-
Pseudo R^2	-	0.39	0.39	0.37
Log-Lik.	-	LL(32)= -1853.18	LL(32)= -1831.05	LL(32)= -1889.02
AIC	-	3770.36	3726.09	3877.28
Wald	$F^*(31,11630)=$ 36.54***	-	-	-
N	11,662	11,662	11,662	11,662

**p<0.05; **p<0.01; ***p<0.001*

+++ To avoid missing data, variables with zero or negative values were transformed as: $\ln(x_j + 1)$. Heteroskedasticity-robust F-statistics are used with the LPM. Probit and Logit model coefficients on the j^{th} continuous covariate represents Average Partial Effects (APE): $N^{-1} \sum_i g(\hat{\alpha}_0 + \mathbf{x}_i'\hat{\boldsymbol{\alpha}} + \mathbf{z}_i{}'\hat{\boldsymbol{\gamma}} + \mathbf{w}_i'\hat{\boldsymbol{\beta}})\hat{\alpha}_j$. Coefficients for the j^{th} binary covariate represent the average difference in probabilities from a change in the binary indicator: $N^{-1}\sum_i\{G(\hat{\alpha}_0 + \hat{\alpha}_j(x_{ji} = 1) + \mathbf{x}_i'\hat{\boldsymbol{\alpha}} + \mathbf{z}_i{}'\hat{\boldsymbol{\gamma}} + \mathbf{w}_i'\hat{\boldsymbol{\beta}}) - G(\hat{\alpha}_0 + \hat{\alpha}_j(x_{ji} = 0) + \mathbf{x}_i'\hat{\boldsymbol{\alpha}} + \mathbf{z}_i{}'\hat{\boldsymbol{\gamma}} + \mathbf{w}_i'\hat{\boldsymbol{\beta}})\}$.

TABLE A.3 – Estimated Marginal Effects from Restricted Binary Choice Models with Pooled Incident Report Data (daily weather control variables omitted)+++

Dep. Variable:	s_i	s_i	s_i	s_i
Coefficient	LPM (robust s.e.)	Probit	Logit	Complementary Log-Log
Intercept	0.30 (0.21)	-	-	-
$\ln mtemp_i$	0.13* (0.06)	-0.18** (0.06)	-0.28*** (0.06)	-0.01 (0.06)
$\ln mprecip_i$	0.06*** (0.01)	0.03** (0.01)	0.03*** (0.01)	0.02* (0.01)
$\ln mminvpd_i$	0.02** (0.01)	0.03** (0.01)	0.04*** (0.01)	0.02 (0.01)
$\ln mmaxvpd_i$	0.05*** (0.01)	0.07*** (0.02)	0.11*** (0.02)	0.01 (0.02)
$\ln dtemp_i$	-	-	-	-
$\ln windspeed_i$	-	-	-	-
$\ln relhum_i$	-	-	-	-
$\ln elev_i$	-0.12*** (0.01)	-0.24*** (0.01)	-0.27*** (0.01)	-0.18*** (0.01)
$\ln wuidist_i$	-0.03*** (<0.01)	-0.03*** (<0.01)	-0.03*** (<0.01)	-0.03*** (<0.01)
$human_i$	0.06*** (<0.01)	0.06*** (0.01)	0.06*** (0.01)	0.05*** (0.01)
$complex_i$	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)
$federal_i$	-0.02*** (<0.01)	-0.09*** (0.01)	-0.11*** (0.02)	-0.06*** (0.01)
$highprep_i$	0.06 (<0.01)	0.09*** (0.01)	0.09*** (0.01)	0.08*** (0.01)
OR_i	0.08*** (0.01)	0.02** (0.01)	0.01 (0.01)	0.03*** (0.01)
WA_i	-0.02* (0.01)	-0.04*** (0.01)	-0.04*** (0.01)	-0.05*** (0.01)
$flame_i$	2.79*** (0.43)	0.36*** (0.28)	0.32** (0.11)	0.36*** (0.01)
$flame_i * \ln mtemp_i$	-0.98*** (0.13)	-0.43*** (0.08)	-0.33*** (0.08)	-0.59*** (0.09)
$flame_i * \ln precip_i$	-0.02 (0.02)	0.01 (0.01)	0.01 (0.01)	0.02* (0.01)
$flame_i * \ln mminvpd_i$	0.08*** (0.02)	0.04** (0.01)	0.03* (0.01)	0.06*** (0.01)
$flame_i * \ln mmaxvpd_i$	0.36*** (0.04)	0.20*** (0.03)	0.16*** (0.03)	0.26*** (0.03)

$flame_i * \ln dtemp_i$	-	-	-	-
$flame_i * \ln windspeed_i$	-	-	-	-
$flame_i * \ln relhum_i$	-	-	-	-
$flame_i * \ln elev_i$	-0.01 (0.01)	0.14*** (0.02)	0.16*** (0.02)	0.10*** (0.02)
$flame_i * \ln wuidist_i$	0.02** (<0.01)	0.02*** (0.01)	0.02** (0.01)	0.02*** (0.01)
$flame_i * human_i$	-0.03** (0.01)	-0.06** (0.02)	-0.06* (0.03)	-0.06*** (0.02)
$flame_i * complex_i$	0.02 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
$flame_i * federal_i$	-0.03*** (0.01)	0.07* (0.03)	0.12* (0.05)	0.02 (0.02)
$flame_i * highprep_i$	-0.03*** (0.01)	-0.11*** (0.02)	-0.12*** (0.02)	-0.09*** (0.01)
$flame_i * OR_i$	-0.14*** (0.01)	-0.08*** (0.02)	-0.07*** (0.01)	-0.08*** (0.01)
$flame_i * WA_i$	0.07*** (0.02)	0.04*** (0.01)	0.04*** (0.01)	0.06*** (0.01)
Skewness coefficient from skewed probit model $(\hat{\delta})$	-	2.35*** (0.48)	-	-
Chow test for structural change across time (H.1)	$F^*(13,15551) = 26.62^{***}$	$\chi^2_{12} = 370.21^{***}$	$\chi^2_{12} = 418.87^{***}$	$\chi^2_{12} = 385.67^{***}$
Unpaired two-sample t-test of total effect of policy change (H.2)	-	$\hat{\Delta} = -0.02$ $t^*(11660) =$ -9.05***	$\hat{\Delta} = -0.02$ $t^*(11660) =$ -9.17***	$\hat{\Delta} = -0.02$ $t^*(15575) =$ -10.36***
Two-sample Wilcoxon Rank-sum test (H.2)	-	$z^* =$ 35.32***	$z^* =$ 37.78***	$z^* =$ 30.55***
R^2	0.189	-	-	-
R^2_a	0.187	-	-	-
Pseudo R^2	-	0.37	0.38	0.36
Log-Lik.	-	LL(26)= -2835.13	LL(26)= -2805.68	LL(26)= -2892.68
AIC	-	5727.79	5663.36	5837.35
Wald	$F^*(25,15551)=$ 73.94***	-	-	-
N	15,577	15,577	15,577	15,577

**p<0.05; **p<0.01; ***p<0.001*

+++ To avoid missing data, variables with zero or negative values were transformed as: $\ln(x_j + 1)$. Heteroskedasticity-robust F-statistics are used with the LPM. Probit and Logit model coefficients on the j^{th} continuous covariate represents Average Partial Effects (APE): $N^{-1}\sum_i g(\hat{\alpha}_0 + \mathbf{x}_i'\hat{\boldsymbol{\alpha}} + \mathbf{z}_i{}'\hat{\boldsymbol{\gamma}} + \mathbf{w}_i'\hat{\boldsymbol{\beta}})\hat{\alpha}_j$. Coefficients for the j^{th} binary covariate represent the average difference in probabilities from a change in the binary indicator: $N^{-1}\sum_i\{G(\hat{\alpha}_0 + \hat{\alpha}_j(x_{ji} = 1) + \mathbf{x}_i'\hat{\boldsymbol{\alpha}} + \mathbf{z}_i'\hat{\boldsymbol{\gamma}} + \mathbf{w}_i'\hat{\boldsymbol{\beta}}) - G(\hat{\alpha}_0 + \hat{\alpha}_j(x_{ji} = 0) + \mathbf{x}_i'\hat{\boldsymbol{\alpha}} + \mathbf{z}_i'\hat{\boldsymbol{\gamma}} + \mathbf{w}_i'\hat{\boldsymbol{\beta}})\}$.

Appendix B: Tables and Figures (Manager-level Panel Data)

TABLE B.1 – DESCRIPTIVE STATISTICS FOR MANAGER-LEVEL PANEL OF INCIDENT REPORT DATA

Variable	Description	Source	Mean (St. Dev.)	Min	Max	N
s_{jt}	=1 if Full Suppression strategy, =0 otherwise	ICS-209	0.89 (0.3)	0.0	1.0	11,792
$wind_{jt}$	Reported windspeed (mph)	ICS-209	10.1 (14.9)	0.0	1025	9,211
$temp_{jt}$	Reported temperature (degrees F)	ICS-209	76.3 (18.0)	0.0	406	9,523
$relhum_{jt}$	Reported relative humidity	ICS-209	30.5 (18.5)	0.0	177	8,742
$elev_{jt}$	Elevation at ignition point (thousand ft.)	PRISM	3.71 (1.9)	-0.1	9.7	11,792
$mtemp_{jt}$	Avg. temperature in month of ignition (degrees F)	PRISM	65.9 (8.9)	20.0	90.0	11,792
$mprecip_{jt}$	Precipitation in month of ignition (inches)	PRISM	0.6 (1.6)	0.0	56.0	11,792
$mminvpd_{jt}$	Minimum recorded vapor pressure deficit in month of ignition (hPa)	PRISM	5.3 (2.9)	0.1	20.3	11,792
$mmaxvpd_{jt}$	Maximum recorded vapor pressure deficit in month of ignition (hPa)	PRISM	30.0 (10.5)	1.2	68.3	11,792
$wuidist_{jt}$	Distance from ignition point to nearest wildland-urban interface zone (thousand meters)	SILVIS	6.1 (6.3)	0.0	47.7	11,361
$complex_{jt}$	=1 if Type 1 or Type 2 incident complexity, =0 otherwise	ICS-209	0.5 (0.5)	0.0	1.0	11,792
$federal_{jt}$	=1 if suppression response by federal agency, =0 otherwise	ICS-209	0.7 (0.4)	0.0	1.0	11,792
$flame_{jt}$	=1 if report filed during or after FY2010 when FLAME reserve funds were available, =0 otherwise	ICS-209	0.3550 (0.4785)	0	1	11,792
$human_{jt}$	=1 if ignition caused by human, =0 if by lightning or unknown cause	ICS-209	0.1 (0.3)	0.0	1.0	11,792
PL_t	National Wildfire Preparedness Level on day of reported ICS-209 form (=1 for	NIFC	2.5 (1.4)	1.0	5.0	11,792

	low preparedness, =5 for high preparedness)					
$highprep_t$	=1 if National Wildfire Preparedness Level on day of reported ICS-209 form is 4 or 5, =0 otherwise	NIFC	0.3 (0.5)	0.0	1.0	11,792
CA_{jt}	=1 if incident occurs in Oregon, =0 otherwise	ICS-209	0.6 (0.5)	0.0	1.0	11,792
OR_{jt}	=1 if incident occurs in Oregon, =0 otherwise	ICS-209	0.3 (0.4)	0.0	1.0	11,792
WA_{jt}	=1 if incident occurs in Washington, =0 otherwise	ICS-209	0.1 (0.3)	0.0	1.0	11,792

TABLE B.2 – Unrestricted Binary Choice Model Results with Panel Data

Dep. Variable:	s_{jt}	s_{jt}	s_{jt}	s_{jt}
Coefficient	Pooled OLS (robust s.e.)	FE (clustered s.e.)	RE (clustered s.e.)	CRE Logit^{+++}
Intercept	1.19***	1.89**	1.60**	-
	(0.33)	(0.69)	(0.56)	
$\ln mtemp_{jt}$	-0.19	-0.36	-0.28	0.11
	(0.10)	(0.21)	(0.18)	(0.15)
$\ln mprecip_{jt}$	0.04**	0.09*	0.08*	0.03**
	(0.01)	(0.04)	(0.03)	(0.01)
$\ln mminvpd_{jt}$	0.04***	0.04	0.03	0.00
	(0.01)	(0.02)	(0.02)	(0.02)
$\ln mmaxvpd_{jt}$	0.11***	0.16*	0.14*	0.11**
	(0.02)	(0.07)	(0.06)	(0.04)
$\ln dtemp_{jt}$	0.04	0.03**	0.03**	0.01
	(0.03)	(0.01)	(0.01)	(0.01)
$\ln windspeed_{jt}$	0.01	-0.01	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.02)
$\ln relhum_{jt}$	0.03**	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
$\ln elev_{jt}$	-0.14***	-0.09*	-0.09**	-0.09***
	(0.01)	(0.04)	(0.03)	(0.03)
$\ln wuidist_{jt}$	-0.04***	-0.01	-0.02*	-0.03**
	(<0.01)	(0.01)	(0.01)	(0.01)
$human_{jt}$	0.08***	0.01	0.02	0.01
	(0.01)	(0.02)	(0.01)	(0.01)
$complex_{jt}$	0.04***	0.06	0.03	0.01
	(0.01)	(0.04)	(0.02)	(0.01)
$federal_{jt}$	-0.01**	-0.04	-0.03	-0.07***
	(0.01)	(0.05)	(0.03)	(0.02)
$highprep_{t}$	0.08***	0.00	0.01	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
OR_{jt}	0.09***	-0.10	-0.03	-0.02
	(0.01)	(0.08)	(0.04)	(0.02)
WA_{jt}	-0.03*	-0.12	-0.06	0.00
	(0.01)	(0.08)	(0.03)	(0.01)
$flame_{jt}$	2.74***	0.63	1.11	-0.85
	(0.59)	(1.60)	(1.27)	(0.63)
$flame_{jt} * \ln mtemp_{jt}$	-0.86***	-0.33	-0.45	-0.54*
	(0.19)	(0.49)	(0.39)	(0.21)
$flame_{jt} * \ln precip_{jt}$	0.03	-0.06	-0.05	-0.02
	(0.02)	(0.06)	(0.05)	(0.02)
$flame_{jt} * \ln mminvpd_{jt}$	0.10***	0.02	0.03	0.08**
	(0.02)	(0.07)	(0.06)	(0.03)
$flame_{jt} * \ln mmaxvpd_{jt}$	0.36***	0.24	0.27*	0.15**
	(0.05)	(0.16)	(0.13)	(0.05)
$flame_{jt} * \ln dtemp_{jt}$	-0.12*	-0.05*	-0.06**	-0.02

	(0.06)	(0.02)	(0.02)	(0.02)
$flame_{jt} * \ln windspeed_{jt}$	0.03**	0.01	0.02	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
$flame_{jt} * \ln relhum_{jt}$	-0.03	0.01	0.00	0.01
	(0.02)	(0.01)	(0.01)	(0.01)
$flame_{jt} * \ln elev_{jt}$	-0.03	0.04	0.01	-0.06
	(0.02)	(0.07)	(0.06)	(0.04)
$flame_{jt} * \ln wuidist_{jt}$	0.04***	0.00	0.00	0.01
	(0.01)	(0.02)	(0.02)	(0.01)
$flame_{jt} * human_{jt}$	-0.02	-0.01	0.00	0.05***
	(0.01)	(0.02)	(0.02)	(0.02)
$flame_{jt} * complex_{jt}$	0.04**	0.02	0.01	0.03*
	(0.01)	(0.04)	(0.03)	(0.01)
$flame_{jt} * federal_{jt}$	-0.05***	-0.02	-0.02	0.02
	(0.01)	(0.03)	(0.03)	(0.04)
$flame_{jt} * highprep_{t}$	-0.06***	0.02	0.01	-0.08***
	(0.01)	(0.03)	(0.03)	(0.02)
$flame_{jt} * OR_{jt}$	-0.12***	-0.17*	-0.15*	-0.02
	(0.02)	(0.07)	(0.06)	(0.02)
$flame_{jt} * WA_{jt}$	0.14***	0.09	0.08*	0.02
	(0.02)	(0.05)	(0.04)	(0.03)
Chow test for structural change (H.1)	$F^*(15,8219) =$ 16.87***	$F^*(15,1904) =$ 2.10**	$\chi^2(15)=$ 44.05***	$\chi^2(12) =$ 52.94***
Unpaired two-sample t-test of total effect of policy change (H.2)	-	-	-	$\hat{\Delta}= -0.03$ $t^*(8249) =$ -15.17***
Two-sample Wilcoxon rank-sum test (H.2)	-	-	-	$z^* =$ 13.94***
R^2 (within)	-	0.152	0.142	-
R^2 (between)	-	0.091	0.128	-
R^2 (overall)	0.202	0.099	0.139	-
R_a^2	0.199	-	-	-
Wald	$F^*(31,8219)=$ 37.10***	$F^*(31,1904)=$ 2.14***	$\chi^2(31)=$ 122.27***	$\chi^2(59) =$ 123.50***
Log. Lik.	-	-	-	LL(64)= -683.78
N	8,251	8,251	8,251	8,251
Joint test of Mundlak terms	-	-	-	$\chi^2(28) =$ 55.01**
Hausman Test	-	-	$\chi^2(31)=$ 328.95***	-
Breusch-Pagan LM Test	-	-	$\chi^2(1)=$ 17,198***	-

**p<0.05; **p<0.01; ***p<0.001;*

$^{+++}$ *Coefficients for the k^{th} binary covariate represent the average difference in probabilities from a change in the binary indicator.*

TABLE B.3 – Restricted Binary Choice Model Results with Panel Data (daily weather controls omitted)

Dep. Variable:	s_{jt}	s_{jt}	s_{jt}	s_{jt}
Coefficient	Pooled OLS (robust s.e.)	FE (clustered s.e.)	RE (clustered s.e.)	CRE Logit+++
Intercept	0.50	0.78	0.80	-
	(0.26)	(0.66)	(0.52)	
$\ln mtemp_{jt}$	0.08	0.02	0.02	0.24*
	(0.07)	(0.20)	(0.16)	(0.10)
$\ln mprecip_{jt}$	0.06***	0.04	0.03	0.01
	(0.01)	(0.03)	(0.03)	(0.01)
$\ln mminvpd_{jt}$	0.03**	0.01	0.02	-0.03*
	(0.01)	(0.02)	(0.02)	(0.01)
$\ln mmaxvpd_{jt}$	0.07***	0.05	0.05	-0.02
	(0.02)	(0.06)	(0.05)	(0.03)
$\ln dtemp_{jt}$	-	-	-	-
$\ln windspeed_{jt}$	-	-	-	-
$\ln relhum_{jt}$	-	-	-	-
$\ln elev_{jt}$	-0.15***	-0.05	-0.06**	-0.06**
	(0.01)	(0.03)	(0.02)	(0.02)
$\ln wuidist_{jt}$	-0.04***	-0.02*	-0.02**	-0.01
	(<0.01)	(0.01)	(0.01)	(0.01)
$human_{jt}$	0.09***	0.04	0.04*	0.01
	(0.01)	(0.02)	(0.02)	(0.01)
$complex_{jt}$	0.03***	0.06	0.02	0.01
	(0.01)	(0.03)	(0.02)	(0.01)
$federal_{jt}$	-0.02***	-0.06	-0.04	-0.08***
	(<0.01)	(0.05)	(0.03)	(0.02)
$highprep_{t}$	0.08***	0.01	0.02	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
OR_{jt}	0.11***	-0.09	-0.02	-0.02
	(0.01)	(0.07)	(0.04)	(0.01)
WA_{jt}	-0.03*	-0.14	-0.07*	-0.03
	(0.01)	(0.08)	(0.04)	(0.02)
$flame_{jt}$	2.91***	2.91**	2.63**	0.35***
	(0.51)	(1.08)	(0.91)	(<0.01)
$flame_{jt} * \ln mtemp_{jt}$	-1.05***	-1.03**	-0.95***	-0.58***
	(0.15)	(0.34)	(0.28)	(0.17)
$flame_{jt} * \ln precip_{jt}$	0.00	-0.01	-0.01	0.00
	(0.02)	(0.04)	(0.04)	(0.01)
$flame_{jt} * \ln mminvpd_{jt}$	0.09***	0.06	0.05	0.07***
	(0.02)	(0.06)	(0.05)	(0.02)
$flame_{jt} * \ln mmaxvpd_{jt}$	0.40***	0.40**	0.38***	0.21***
	(0.05)	(0.12)	(0.10)	(0.04)
$flame_{jt} * \ln dtemp_{jt}$	-	-	-	-

$flame_{jt} * \ln windspeed_{jt}$	-	-	-	-
$flame_{jt} * \ln relhum_{jt}$	-	-	-	-
$flame_{jt} * \ln elev_{jt}$	-0.01	-0.04	-0.04	0.06*
	(0.02)	(0.06)	(0.05)	(0.03)
$flame_{jt} * \ln wuidist_{jt}$	0.01*	0.01	0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.01)
$flame_{jt} * human_{jt}$	-0.04**	0.01	0.00	0.04*
	(0.01)	(0.03)	(0.03)	(0.02)
$flame_{jt} * complex_{jt}$	0.04***	0.01	0.01	0.04**
	(0.01)	(0.04)	(0.03)	(0.02)
$flame_{jt} * federal_{jt}$	-0.03***	-0.02	-0.02	-0.01
	(0.01)	(0.04)	(0.03)	(0.04)
$flame_{jt} * highprep_{t}$	-0.04***	0.02	0.01	-0.04**
	(0.01)	(0.03)	(0.02)	(0.01)
$flame_{jt} * OR_{jt}$	-0.13***	-0.18**	-0.16***	-0.04
	(0.02)	(0.06)	(0.05)	(0.02)
$flame_{jt} * WA_{jt}$	0.10***	0.06	0.06	0.03
	(0.02)	(0.05)	(0.04)	(0.02)
Chow test for structural change (H.1)	$F^{*}(12,11584) =$ 25.63***	$F^{*}(12,2452) =$ 3.42***	$\chi^2_{12} =$ 53.18***	$\chi^2_{12} =$ 90.64***
Unpaired two-sample t-test of total effect of policy change (H.2)	-	-	-	$\hat{\Delta} = -0.04$ $t^{*}(11608) =$ -19.88***
Two-sample Wilcoxon rank-sum test (H.2)	-	-	-	$z^{*} =$ 18.99***
R^2 (within)	-	0.137	0.130	-
R^2 (between)	-	0.125	0.163	-
R^2 (overall)	0.211	0.114	0.157	-
R_a^2	0.209	-	-	-
Wald	$F^{*}(25,11584)=$ 74.67***	$F^{*}(25,2452)=$ 3.17***	$\chi^2(25)=$ 152.41***	$\chi^2(47)=$ 282.20***
Log. Lik.	-	-	-	LL(52)= -1110.85
N	11,610	11,610	11,610	11,610
Joint test of Mundlak terms	-	-	-	$\chi^2(22)=$ 16.28***
Hausman Test	-	-	$\chi^2(25)=$ 248.99**	-
Breusch-Pagan LM Test	-	-	$\chi^2(1)=$ 31,982***	-

**p<0.05; **p<0.01; ***p<0.001;*

+++ *Coefficients for the k^{th} binary covariate represent the average difference in probabilities from a change in the binary indicator.*

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GENERAL CONCLUSION

Chapters 1 and 2 of this dissertation have presented alternative microeconomic frameworks which provide testable hypotheses and which can explain the observed patterns of larger expenditure shares on fire suppression. In Chapter 4, I tested several of these hypotheses through a discrete choice econometric model of incident managers’ decisions. My results test two of the alternative hypotheses derived in first two chapters: 1) reserve mechanisms which lower the effective marginal cost of suppression may increase the adoption of full suppression strategies (potentially increasing the demand for suppression resources and suppression costs), but this may not outweigh the effects of policy guidance which encouraged more frequent adoption of “let-burn” strategies, and 2) fire events occurring farther from residential developments are less likely to be fully suppressed; reflecting a preference for avoiding a truncation of right-tailed distributions of net value change over fires that burn far from human populations. Further research on the degree of risk aversion and its measurement may be needed to properly design a corrective contractual mechanism between local land management agency administrators and contracted incident commanders (a call for research on contract design for suppression service providers is also discussed by Donovan et al., 2008, and may be a natural extension to the game-theoretic models presented in this dissertation). Budgetary institutions and risk attitudes of both public and private land managers will become especially important factors for determining the success of fire risk mitigation programs and incentive compatible mechanisms. Overall, this line of research is useful for agencies seeking to improve fire management outcomes via more efficient designs of federal or state contracts granted for suppression services.

Another important direction for further research relates to the dynamics of the fire management expenditure shares considered in Chapters 1 and 2. The dynamics of a multiple-input system with prevention or pre-suppression efforts has not been formalized in the forest economics literature, despite similar specifications of dynamic models which detail the evolution of budgets allocated across preventative and reactionary management programs for other forest disturbance agents like the emerald ash borer in the Rocky Mountain region (Berry et al., 2017). The chapters in this dissertation carefully considered the tradeoffs between pre-suppression and suppression programs and the socioeconomic factors which drive the allocation at the regional and national levels. There remains a gap in this line of research regarding the time path of optimal pre-suppression budgets in response to current allocations. This dissertation has also left open the question of unstable equilibrium outcomes: under what conditions will the fire management system not evolve towards a stable state, such that suppression costs and damages never stabilize but continue to grow unabated? Optimal control theory and stochastic dynamic programming methods will be essential for further formulation of the suppression allocation problem, and the propensity for the fire management system to evolve differently over time under alternative allocations of annual budgets and under alternative fire regimes.

In Chapter 3 of this dissertation, I showed how the optimal design of forest-based taxes can shift with more widespread adoption of carbon offset markets. Specifically, I have shown that when carbon markets are adopted by the representative timberland owner subject to a disturbance risk, the state planner’s optimal taxation strategy is to rely solely on the use of a per-acre fee on land holdings rather than a tax per-unit volume of harvested timber. In contrast, when the representative timberland owner does not participate in a carbon offset market, state tax planners are constrained to a second-best equilibrium via the application of per-unit volume taxes on harvest in lieu of the acre-based land tax. In both cases, we considered how the state planner's provision of wildfire protection can impact the risk-adjusted discount rate applied by private timberland owners. When fire protection expenditures increase, the fire arrival rate decreases such that landowners apply a lower risk-adjusted discount rate to their land's future cash flows. This has the effect of lengthening rotation ages and increasing land values. Importantly, it permits a second-best equilibrium outcome when carbon offset markets are unavailable since the corrective (Pigouvian) harvest tax is unable to generate sufficient revenue to compensate landowners via fire protection for the drop in net stumpage values that accompany the harvest tax. We have used a representative agent framework to arrive at these results, so additional research may seek to investigate how optimal taxation may change with limited adoption across a group of timberland owners. Further research may also investigate how alternative tax instrument might perorm in this setting here carbon sequestration has value and disturbance risk is present (such as ad valorem harvest taxes or timber taxes). Furthermore, we have left open the question about unknown risk attitudes, which can place additional constraints on the planner's optimal taxation problem.

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