

CHARACTERIZING INCENTIVES: AN INVESTIGATION OF WILDFIRE RESPONSE
AND ENVIRONMENTAL ENTRY POLICY

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Abstract

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Policy makers face complex situations involving the analysis and weighting of multiple incentives that complicate the design of natural resource and environmental policy. The objective of this dissertation is to characterize policy makers' incentives, and to investigate the consequences of those incentives on environmental and economic outcomes in the context of wildfire management and environmental policy.

Wildfire management occurs in a dynamic uncertain environment and requires the coordination of multiple management levels throughout the course of a fire season. Over the course of a wildfire, management teams allocate response resources between suppression of fire growth and protection of valuable assets to mitigate damage with minimal regard for cost. I develop a model of wildfire resource allocation to show that 1) wildfire managers face the incentive to protect residential structures at the expense of larger and more costly fires, and 2) response resources are transferred to fires with more threatened structures constraining the set of resources available to manage other fires in the region. I find empirical evidence to support the predictions of this model with theoretically consistent regression models of wildfire duration, size, and cost using data from U.S. wildfires that occurred between 2001 and 2010. These results imply that continued housing development of wildland prone to wildfire will 1) further distort management incentives, 2) lead to larger and more expensive

fires, and 3) provide support for fees on rural homeowners.

Governments facing political opposition to renewable energy subsidies may resort to augmenting the fixed cost of entry in order to induce environmental outcomes. In global markets, one government's entry policy creates either positive or negative pecuniary externalities in other regions. I develop a two-region model to investigate the behavior of rival governments setting strategic entry policy, and the subsequent impacts on welfare. The results indicate that competition between the rival governments prevents the social optimal level of entry and suggests a role for international environmental agreements.

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Dedication

I dedicate this dissertation to Marissa Alexia, who
brings out the best in me.

Chapter 1

Introduction

Economics offers several clear policy prescriptions for managing natural resources and environmental externalities. It is efficient to exploit a resource until the marginal costs exceed the marginal benefits. When externalities exist, a social planner can increase economic efficiency in competitive markets by discouraging negative externalities with taxes or quotas, or encouraging positive externalities with subsidies and mandates. However, the world in which government agents create and carry out policy is fraught with uncertainty, competing incentives, and strategic behavior. These factors, among others, may influence the design and execution of policy, which ultimately impact economic and environmental outcomes.

The goal of policy design and analysis is to identify the mechanism through which policy alters behavior. Economic models of policy are designed to capture the factors that motivate agents in order to predict how a policy will affect economic outcomes. However, the factors that motivate agents are not always clear to the researcher developing the model. The researcher's choice of model assumptions may have dramatic effects on the model's predicted outcomes.

The objective of this dissertation is to investigate the factors that influence the design and implementation of natural resource and environmental policy in wildfire management and firm entry in the presence of positive external benefits. This dissertation is comprised of three distinct essays woven together by the manner in which I incorporate competing incentives and strategic behavior into theoretical models to analyze policy. In two of the essays, I develop a theory of wildfire response to characterize the incentives of wildfire management and investigate the impacts of these incentives on wildfire duration, cost and size. In a

third study, I analyze the strategic use of entry policy by governments who compete for the location of firms that produce a good with positive external benefits. These studies provide unique insights into analyzing policies in the context of uncertainty, competing incentives, and strategic behavior.

1.1 Wildfire Management

Wildfire management is an economic problem because, despite its natural occurrence, it causes property damage and impacts the utilization and quality of other natural resources (i.e., air and water). Since wildfire does not respect property boundaries, and often involves costly coordination of many response resources, management responsibilities have largely been assumed by the government. However, management objectives are unclear and may depend on the environment, expectations, and political factors. Over the past decade, wildfire management costs have risen dramatically highlighting the need for economic analysis of policy and implementation (Gebert et al., 2008).

Recent wildfire research has identified three important contributors to rising wildfire costs: prior policy, climate change, and the expansion of the wildland urban interface. Until recently, the prevailing federal response strategy has been to aggressively suppress any wildfire as quickly as possible (Schoennagel, Veblen, and Romme, 2004; Covington and Moore, 1994). Researchers argue that because ecosystems have evolved to rely on regular wildfire cycles, suppression of all fire has caused a significant accumulation of fuel. This additional fuel turns what may have been low intensity fires, which are not necessarily destructive, into very intense fires that are difficult and expensive to manage. Climate change models predict changing and more volatile weather patterns, which may increase wildfire intensity and require more costly management (Fried, Torn, and Mills, 2004; Stephens and Ruth, 2005; Westerling et al., 2006). Development of wildland is also receiving significant attention

from researchers. To the extent that wildfire management prioritizes residential structure protection, homes built in the wildland urban interface (WUI) increase the need for costly management (Donovan, Noordijk, and Radeloff, 2004; Liang et al., 2008; Gude et al., 2013; Yoder and Gebert, 2012; Calkin et al., 2013).

In chapter 2, I study how an increase in the number of threatened structures impacts wildfire duration, cost, and size. I develop a dynamic model of wildfire response in which management teams face an intertemporal tradeoff between protection of threatened assets and suppression (an investment in future protection). An increase in the number of threatened assets increases the marginal benefit of protection relative to suppression. The lack of suppression allows the fire to grow larger, burn longer, and ultimately, cost more to extinguish than it otherwise might. I find support for this theoretical prediction with a trivariate hazard model of wildfire duration, cost, and size.

In chapter 3, I focus on the interaction between individual and regional fire manager. I extend the dynamic model of wildfire response developed in chapter 2 to distinguish individual and regional fire managers in order to characterize a set of estimable resource allocation equations. I then estimate a theoretically-consistent econometric model of response resource allocation equations, which are used to generate instruments in a set of second-stage hazard regressions of duration, cost, and size.

The results in both studies show that threatened structures lead to larger and more expensive wildfires. My contribution to this literature is threefold: 1) I provide a unique theory of wildfire response that identifies an economic mechanism causing longer, larger and more expensive wildfires; 2) I develop and implement a trivariate hazard model in which correlation between wildfire duration, cost, and size is captured by a trivariate latent variable; and 3) I estimate a set of response resource allocation equations to show that threatened residential structures significantly impact the number of resources committed to a given wildfire.

1.2 Environmental Entry Policy

Governments may use a variety of price and quantity instruments to regulate the externalities arising from the production and consumption of goods and services. However, permanent regulation may require legislative approval, which has proven a formidable obstacle in some countries (Stokes, 2013). Governments might instead take action to modify the administrative costs of entry in order to facilitate their desired level of entry (Cato, 2010). Recent efforts to promote renewable energy in the U.S., Europe, and China have included reduced fees, favorable loans, and grants to firms entering the production market or expanding capacity. These entry policies are currently at the root of several trade disputes between U.S. and Chinese solar panel manufacturers (Bayaliyev, Kalloz, and Robinson, 2011).

The environmental economics literature has extensively studied the implementation of price and quantity policy instruments. In theory, policy instruments such as taxes, subsidies, and quotas can induce the socially optimal level of production and consumption, under certain conditions (Baumol and Oates, 1988). However, policy design becomes more complicated in the presence of additional externalities arising from imperfect competition and international trade (Barrett, 1994; Ulph, 1996; Kennedy, 1994).

In chapter 4 I extend the theoretical literature on environmental policy by analyzing the use of entry taxes, subsidies, and permit restrictions to regulate an industry with endogenous market structure in which firms produce a good that yields external benefits. A regulator then sets a policy to induce the number of firms that maximizes social welfare. I compare the policy implications of two regulatory structures. In one case, I consider a single regulator that has jurisdiction over all firms. In a second case, I consider two regions, each with a respective regulator who has jurisdiction over firms that choose to locate within its region. I show that the existence of a rival regulator creates pecuniary externalities that prevent both regulators from inducing their respective domestically optimal level of entry. These results

highlight the importance of international competition between regulators when designing environmental policy.

Chapter 2

Wildfire Hazards

2.1 Introduction

Disaster managers allocate resources to accomplish a set of objectives in a highly uncertain environment. While the specific objectives of a manager vary depending on the type of disaster, cost minimization and damage mitigation receive significant attention. Managers often face tradeoffs between forms of response effort used to accomplish their objectives. Disaster containment may limit the growth or extent of the disaster while protection may reduce the damage to specific assets. Managers of infectious disease outbreak, invasive species, oil spill, and nuclear contamination all face tradeoffs between containment and protection of threatened assets. The allocation decisions made throughout the course of a disaster inevitably impact final outcomes such as the damage and cost of a disaster.

Wildfire is a destructive and complex form of disaster in the U.S., and the world, with recent U.S. federal management costs exceeding \$2 billion annually (Gebert et al., 2008). Management of a wildfire often takes place over the course of several days or even weeks. Decisions are made each day based on new and updated information relating to fire development, including past and present fire behavior, weather changes, differences over space and time in values at risk, and numerous other factors. The dynamic spatiotemporal path of the fire is affected by these environmental factors, and the management decisions, over the course of the fire, until its completion. These environmental factors and resource allocation decisions affect final fire outcomes by affecting spatial outcomes at any point during the response effort.

The wildland urban interface (WUI) has grown significantly over the past several decades, and wildfire managers find themselves devoting more response resources to structure protection than ever before (Mercer and Prestemon, 2005). A growing population and a desire to live near forests have drawn people to build structures in areas inherently susceptible to wildfire. These structures are often high-value homes and cabins. Wildfire managers face significant political pressure to protect these structures, which may come at the expense of other management objectives (Troyer et al., 2003).¹

This paper develops an economic theory of disaster response to characterize the impact of threatened assets on disaster outcomes. A manager chooses containment and protection to minimize losses subject to a stochastic process representing the disaster. I adapt the theory of disaster response to wildfire management, and formulate three hypotheses: when assets are threatened during the course of a wildfire, the expected 1) duration, 2) final fire size, and 3) total suppression cost increases. I jointly estimate a trivariate hazard model (variously known as duration, time-until-failure, and event history model) of wildfire duration, size, and suppression cost. I utilize daily situation report data on individual wildfires in the United States from 2001 to 2008 to estimate a trivariate hazard model of wildfire duration, size, and cost. The correlation between outcomes is captured through a jointly distributed latent variable.

There exists a rich literature on disaster management that spans several fields of social science. Recent epidemiological-economic models of infectious disease outbreak recognize tradeoffs between treatment of affected populations and prevention through vaccination or distancing (Fenichel et al., 2011; Ludkovski and Niemi, 2010). Other disaster management problems with similar tradeoffs include invasive species, oil spill, and nuclear meltdown

¹Quinn (2005) recounts the management actions taken during one of Oregon’s largest wildfires in history, the Biscuit Fire, which ultimately burned over 500,000 acres. After nearly two weeks of unsuccessful containment, response resources were reassigned to protect structures on the fire’s East side, allowing the fire to grow on the unattended North side.

(Finnoff et al., 2005; Bassey and Chigbu, 2012). Altay and Green (2006) provide a survey of the operations research literature on disaster management in which they categorize four stages of disaster operations management: preparedness, mitigation, response, and recovery. Gebert et al. (2008) discusses these phases of management as they pertain to wildfire suppression. This paper focuses solely on the response phase of the management process in order to understand the implications of response decisions, throughout the event, on final outcomes.

There have been numerous efforts to estimate the economic relationships and tradeoffs embodied in wildfire management, as well as forecasts of suppression costs, fire size, and other outcome measures. Mercer and Prestemon (2005) summarize some of these existing studies, including models of fire ignition rates or ignition risk, individual or aggregate fire extent (e.g. area burned), fire effects models (outcomes of other metrics such as fire intensity or damage), and combinations of these. Some studies develop models based on aggregate level fire and suppression data (Abt, Prestemon, and Gebert, 2008; Prestemon et al., 2008; Cardille, Ventura, and Turner, 2001), and others focus on data at the individual fire level (Holmes, Huggett, and Westerling, 2008; Butry, Gumpertz, and Genton, 2008; Liang et al., 2008; Gebert, Calkin, and Yoder, 2007; Gude et al., 2013). Of these studies Liang et al. (2008) and Gude et al. (2013) find evidence that threatened residential property effect suppression costs. Prestemon et al. (2008) and Butry (2009), among others, focus on the relationship between ex ante wildfire risk mitigation and wildfire outcomes. Another line of research has integrated physical spatiotemporal spread models with suppression (Fried, Gilles, and Spero, 2006; Butry and Donovan, 2008; Petrovic and Carlson, 2012; Petrovic, Alderson, and Carlson, 2012). While these models provide useful information on the interaction between resource allocation and fire spread, they do not capture the disaster manager's response to economic trade offs during the response effort.

While disaster response and wildfire outcomes have been analyzed with linear regression

and count models, no studies have used hazard models, which are well-suited to characterize the dynamic development of wildfire. Hazard models exploit the variation in time-varying covariates over the course of an event and provide the researcher with information on the cumulative effects on the probability of an outcome. Economists have used hazard models to study factors influencing employment spells, marriage duration, and mortgage default (Meyer, 1990; Bennett, Blanc, and Bloom, 1988; Shumway, 2001). In the medical literature, hazard models are commonly used to compare the efficacy of treatments, and in some studies, multivariate extensions have been developed to account for correlation in the disease treatment of twins (Andersen et al., 1997; Wienke et al., 2005). The most similar empirical model of wildfire to date is Finney, Grenfell, and McHugh (2009), who propose a generalized linear mixed-model (GLMM) of wildfire containment focused on intervals of low- and high-spread. The trivariate hazard model provides probabilistic information on containment in terms of fire size and cost in addition to duration.

This paper contributes to the literature on disaster and wildfire response as well as empirical hazard models. I have found no published research to date that fully utilizes daily observations over the course of a cross-section of wildfires to estimate a dynamic economic/physical model of response beyond Finney, Grenfell, and McHugh (2009). I derive the components of a hazard model from the theory of disaster response, and estimate a seemingly-unrelated-regression-like system of three equations by maximum simulated likelihood. This estimator accounts for unobserved fire-specific effects and improves the efficiency of the parameter estimates. The proposed estimation procedure is similar to the seemingly-unrelated-Poisson model of King (1989) and seemingly-unrelated-negative-binomial model of Winkelmann (2000).

I find evidence to support my hypotheses that an increase in the number of threatened assets raises the expected duration, size, and cost of wildfires. In the model, response managers devote resources to asset protection at the expense of overall suppression when the

number of threatened assets rises. As resources are diverted from suppression, the fire grows and becomes more difficult to suppress. The resulting fire persists longer than it would have had resources maintained previous suppression efforts. The results of this analysis suggest that as the WUI continues to grow, federal and state policies that limit or discourage the expansion of the wildland urban interface may be justified.

The paper proceeds as follows. Section 2.2 develops a stylized model of disaster response management and the connection to empirical hazard models. Section 2.3 provides a description of the data I use for the analysis. Section 2.4 provides the results and discussion. Section 2.5 concludes the paper.

2.2 A Theory of Wildfire Response

Consider a wildfire a self-perpetuating stock of energy that evolves over time.² Like the stock of a renewable resource, the fire persists as long as the stock of energy remains above the minimum threshold necessary to sustain exothermic reaction. In addition to human management efforts, environmental factors, such as weather, fuel, and geography, may influence the rate of growth (decline) of the energy stock. Eventually the energy stock falls below the physical threshold, and the fire is extinguished.

A management team chooses two forms of management effort at time t : protection effort, which reduces the probability of damage to specific values at risk³; and suppression effort, which curtails the overall growth of the fire. Protection can be thought of as intensive asset protection and suppression as extensive asset protection.⁴ Fire lines that span large sections

²While energy is a flow in the physical sense, I use the term stock to remain consistent with the language of dynamic modeling. The stock of energy should be interpreted as a snapshot of the energy expended by the wildfire at any point in time.

³Petrovic, Alderson, and Carlson (2012) develops a simulation-based model of fire spread where suppression reduces the probability that the fire persists in any given cell.

⁴These notions of suppression and protection are conceptually distinct from the spillover and direct effects of mitigation efforts developed in Butry and Donovan (2008). In their model, private agents undertake ex-ante mitigating actions to reduce the probability of own-home ignition, which is a function of mitigating

of the fire front will stop the growth of the fire along that front. If effective, the lines will limit the spatial extent of the fire.

Modern wildfire management is an organizationally complex endeavor. Response to any single fire may involve the cooperation of numerous federal, state, local, and private organizations. The coordination of resources across many fires during a busy fire season exacerbates the resource allocation problem. I summarize the goals of reducing costs, $c(t)$, and damage to values at risk, $d(t)$, in the management team's loss function⁵

$$\ell(c(t), d(t), t). \quad (2.1)$$

Losses are increasing in both costs and damage. The general loss function provides flexibility with regard to the weight (marginal losses) of costs and damage, and may be interpreted more generally as a disutility function.⁶

Costs are given by a linear cost equation at time t ,

$$c(t) = s_f(t)(w_f + w_f^o(t)) + s_d(t)(w_d + w_d^o(t)) \quad (2.2)$$

where $s_f(t)$ is suppression effort, $s_d(t)$ is protection effort, w_i is the constant market price of effort $i = \{f, d\}$, and $w_i^o(t)$ is the opportunity cost of effort $i = \{f, d\}$. I assume that the market price of response resources is constant over the fire duration because government agencies often contract resources for the year so the per unit cost is known a priori. The opportunity cost of resources depends on their availability within a geography, which may

actions undertaken by neighbors.

⁵Lowercase symbols are used to represent instantaneous flows at any given point in time whereas capital symbols denote an accumulation of the stream of those flows. The variable definitions are contained in Table 7 of the appendix.

⁶This feature is important to modeling disaster response because, as Troyer et al. (2003) suggests with regard to wildfire, management teams do not always equate a dollars worth of response with a dollars worth of damage. The loss function may also account for a risk averse fire management team; although, risk aversion is not necessary to obtain the results below.

vary over the course of a fire. These opportunity costs are due to scarcity of quasi-fixed capital during times of high wildfire activity within the region over which response resources are deployed.

Damage is equal to the product of a vector of threatened asset values, the number of threatened assets per acre, and the acres burning at time t ,

$$d(t) = \boldsymbol{\nu}(t) \cdot \frac{\mathbf{y}(t)}{s_d(t)} \cdot a(t) \quad (2.3)$$

where $\boldsymbol{\nu}(t)$ is a $1 \times J$ vector of threatened asset values measured in dollars, $\mathbf{y}(\cdot)$ is a $J \times 1$ vector where each element represents the number of threatened assets per acre corresponding to a particular asset type j , and $a(t)$ is the instantaneous flow of burning area at any point in time t . One may think of $a(t)$ as the contribution to fire size of the fire front as it moves through space. I assume that assets are at risk of destruction at time t , and depending on the level of protection, are destroyed or survive at period $t - \Delta t$.⁷ Threatened asset values, $\boldsymbol{\nu}(t)$, may include assets such as endangered species habitat, watersheds, and marketable timber. Protection effort, $s_d(t)$, effectively reduces the concentration per acre of threatened asset values across a given landscape.⁸

The instantaneous growth in fire size at any given point in time t is given by

$$a(t) = a(\mathbf{z}(t), f(t), t). \quad (2.4)$$

where $\mathbf{z}(t)$ is a vector of exogenous geographic and environmental characteristics such as vegetation and weather.

The energy stock of the fire is $f(t)$. The fire stock evolves according to a stochastic

⁷This assumption implies that $d(t)$ represents the level of damage that the fire manager will experience in between states t and $t - \Delta t$.

⁸An alternative, but equally valid, interpretation is that $s_d(t)$ reduces the probability that a threatened asset is destroyed at time t . This alternative interpretation is qualitatively similar to the weighted area protection measure developed by Kirsch and Rideout (2005).

process represented by the distribution function

$$G(f' \mid f(t), s_f(t), \mathbf{z}(t)) = \int_0^{f'} g(q \mid f(t), s_f(t), \mathbf{z}(t), t) dq \quad (2.5)$$

where $f' = \lim_{\Delta t \rightarrow 0} f(t + \Delta t)$ is the energy stock at the next moment in time. The distribution is conditional on the current level of energy, $f(t)$, exogenous environmental and geographic characteristics, $\mathbf{z}(t)$, and the amount of suppression effort, $s_f(t)$.⁹ By definition, $s_d(t)$ has no impact on $G(\cdot)$ as an approximation.¹⁰ The distribution is lower bounded by zero because the stock of energy must be positive. Suppression effort and exogenous conditions shift the mass of the density over different levels of f depending on whether the variable encourages or discourages growth of the fire stock.¹¹ I assume that the mass of the density shifts over lower values of f when $s_f(t) \geq 0$ increases. The impact of the elements of the vector $\mathbf{z}$ may affect $G(\cdot)$ differently. For instance, high wind $z_1 \in \mathbf{z}$ and steep terrain $z_2 \in \mathbf{z}$ may shift the mass of $G(\cdot)$ over higher values of f while increased humidity $z_3 \in \mathbf{z}$ may shift the mass of $G(\cdot)$ over lower values of f .¹²

The initial fire stock, $f(0) = f_0$, is observed by the management team at the date of discovery and is strictly positive. The wildfire continues to burn until the stock of energy falls below $\bar{f}$ at which point the fire is terminated and the response effort is effectively over.¹³ Therefore, a fire begins *iff* $f_0 > \bar{f}$.

The management team's problem is formalized in the recursive Hamilton-Jacobi-Bellman

⁹Fenichel et al. (2011) and Fraser et al. (2004) use a similar notion of stochastic evolution to model the spread of infectious disease throughout a population.

¹⁰For example, suppose resources were used to remove vegetation and create a perimeter around a threatened structure. These actions would have a minimal impact on the overall energy content of an established wildfire.

¹¹Similarly, Pich, Loch, and De Meyer (2002) formulate a model in which project managers choose actions that impact the probability of event outcomes.

¹²Fenichel et al. (2011) develop a model of infectious disease in which the probability of transmission – growth in the disease stock, analogous to the energy stock – is a function of contact with infected individuals. However, individuals choose their level of contact, and thus, affect the probability of disease spread.

¹³Note that $\bar{f}$ is the level of energy above which supports exothermy at any point in $a(t)$.

equation

$$\begin{aligned}
V(f(0), 0) &= \min_{s_d, s_f \geq 0} \left\{ \ell(c(t), d(t), t) + E_t \left\{ V' \right\} \right\} \\
&= \min_{s_d, s_f \geq 0} \left\{ \ell(c(t), d(t), t) + \int_0^\infty V' g(f' \mid f(t), s_f(t), \mathbf{z}(t)) df' \right\} \quad (2.6)
\end{aligned}$$

where $V(\cdot)$ is the value function and $V' = \lim_{\Delta t \rightarrow 0} V(f(t + \Delta t), t + \Delta t)$.¹⁴ The objective function is defined by equation (2.1) and the components, costs and damage, by equations (2.2) and (2.3), respectively. Because wildfire events take place over short time horizons, I assume the discount rate to be approximately zero, and omit it to reduce notational clutter. The probability density function $g(f')$ is defined in equation (2.5). Suppression and protection effort (s_f and s_d) are lower bounded at zero.¹⁵

The terminal condition determines the end of the response effort which occurs when the fire's stock of energy falls below an exogenously determined threshold $f(T) = \bar{f}$. Therefore, T is a random variable with the following distribution at any point in time t

$$\begin{aligned}
G(\bar{f} \mid s_f(t), \mathbf{z}(t), f(t), t) &= \Pr(f' \leq \bar{f} \mid s_f(t), \mathbf{z}(t), f(t), t) \\
&= \Pr(T \in (t, t + \Delta t] \mid s_f(t), \mathbf{z}(t), f(t), T \geq t). \quad (2.7)
\end{aligned}$$

Equation (2.7) states that the probability of the fire's energy stock falling below the critical value $\bar{f}$ is equal to the probability that the response effort ends, T , in the next interval of time. This relationship effectively connects the model of disaster response to an empirical hazard model. Before I develop this connection further, I derive testable hypotheses regarding the impact of threatened assets on expected duration and expected size of wildfires.

¹⁴Management effort is assumed to begin at the date and time of fire discovery $t = 0$.

¹⁵A degenerative case would entail a fire with no possibility of damage and thus no required effort.

2.2.1 Threatened Assets

As the wildland urban interface continues to grow, wildfire management teams face increasingly difficult tradeoffs between suppression and protection when confronted with threatened assets. I am interested in the impact of a sudden¹⁶ increase in the number of threatened assets at any point in time, t , on the final outcomes duration, T , total cost, $C(T)$ and total size $A(T)$, where $C(t) = \int_0^t c(\tau)d\tau$ from equation (2.2) and $A(t) = \int_0^t a(\tau)d\tau$ from equation (2.4). I summarize the primary theoretical results of this study in the following propositions.

Proposition 1. *An increase in the number of threatened assets, $\mathbf{y}(t)$, at time t leads to longer expected wildfire duration when the loss function is separable in costs and damages.*

Proof. To prove this proposition, I demonstrate that an increase in the number of a single type of threatened asset,¹⁷ $y_1 \in \mathbf{y}$ at any time t during the response effort, increases the expected wildfire duration $E_t\{T\}$. Recall that T is directly related to the distribution $G(\cdot)$ through equation (2.7). By assumption, $dg(f')/ds_f < 0$ and $dg(f')/ds_d = 0$ which imply that only suppression reduces the expected level of the fire's energy stock because protection reduces the density of a given asset without substantially reducing the fire stock. From the system of first-order conditions, suppression is decreasing in the number of threatened assets $ds_f/dy_1 < 0$ and protection is increasing in the number of threatened assets $ds_d/dy_1 > 0$ (see appendix A.1 for derivation). Therefore, a sudden increase in the number of threatened properties, $y_1' > y_1$ *ceteris paribus*, causes the management team to shift resources from suppression, s_f , to protection, s_d , which reduces the probability that $f' < \bar{f}$ and thus increases $E_t\{T\}$. $\square$

¹⁶I choose this language to make the point that during a response effort, conditions may change such that residential properties become threatened. The dataset explicitly quantifies the number of threatened structures at various points throughout the response effort.

¹⁷Let y_1 represent residential property, one of the highest valued assets per unit space that managers protect.

Proposition 2. *An increase in the number of threatened assets, $\mathbf{y}(t)$, at time t leads to a larger expected wildfire size when the loss function is separable in costs and damages.*

Proof. There are two compounding effects that lead to the result $dE\{A(T)\}/dy_1 > 0$: the longer expected duration of a fire (from proposition 1), and the larger energy stock throughout the remaining duration leads to a larger area burned. The first effect follows from the dependence of final fire size on $E_t\{T\}$. I define cumulative area burned at time t as $A(t) = \int_0^t a(\tau) d\tau$ from equation (2.4). Therefore, at any point in time t , the expected area can be separated into two parts: the known area burned up until time t , and the area expected to burn during the remaining duration of the fire.

$$E_t\{A(T)\} = \int_0^t a(\mathbf{z}(\tau), f(\tau), \tau) d\tau + E_t\left\{\int_t^T a(\mathbf{z}(\tau), f(\tau), \tau) d\tau\right\} \quad (2.8)$$

where the fire size at t is known to the management team. Proposition 1 shows that if $y_1(t)$ increases at any point in time, $E_t\{T\}$ increases, which implies that the second portion of equation (2.8) becomes unambiguously larger, *ceteris paribus*.

The second effect follows from the larger fire on the interval (t, T) . By assumption, $da(t)/df(t) > 0$ and $dg(f')/ds_f(t) < 0$, which together with $ds_f(t)/dy_1(t) < 0$, imply that

$$a(\mathbf{z}(t), f(y_1(t), t), t) < E_t\{a(\mathbf{z}(\hat{t}), f(y_1(\hat{t}), \hat{t}), \hat{t})\} \quad \forall \hat{t} \in (t, T). \quad (2.9)$$

Equation (2.9) implies that the expected fire size is larger at all points in time after the increase in y_1 . In summary, the rise in the number of threatened assets increases the expected area through two channels: the dependence of $A(t)$ on T and the higher expected fire size at all points on the interval (t, T) . $\square$

These analytical results are consistent with the simulation results reported in Fried, Gilliss, and Spero (2006) who find evidence that larger fires are expected when response

resources are diverted to protect structures during initial attack.

While fire size and duration are expected to increase with an increase in the number of threatened assets, the impact on cumulative costs is ambiguous in the model. This result is confounded by the relative prices and magnitudes of change of suppression and protection effort. As resources are shifted from suppression to protection ($ds_f/dy_1 < 0$ and $ds_d/dy_1 > 0$), total cost rises at any point in time if expenditure on protection is greater than on suppression

$$|s_d(t)(w_d + w_d^o(t))| > |s_f(t)(w_f + w_f^o(t))|.$$

Given the explicit costs are constant throughout the response effort, the relative price of the resources depends on the opportunity cost. If the potential marginal damage to threatened assets is large enough, the management team will find it optimal to increase protection such that total costs rise. Additionally, the expected duration of a fire increases (proposition 1), which implies a longer response effort that may or may not require the use of costly resources.

Proposition 3. *Cumulative costs $C(T) = \int_0^T c(t) dt$ rise in response to an increase in the number of threatened assets y_1 when the loss function is separable in costs and damages, and if one or both of the following hold:*

1. *increased expenditure on protection is larger than the savings on suppression over (t, T) ,*
2. *expenditure over the excess duration (proposition 1) exceeds any expenditure reduction due to substitution from suppression toward protection.*

The theory does not provide a definitive prediction of the impact of threatened assets on cost. However, the presence of any valuable asset during the extended duration (proposition 1), would induce a fire manager to apply costly response effort implying larger final costs.

2.2.2 Hazard Model

I now draw the connection between the stochastic dynamic program and empirical hazard models. The following section demonstrates how fire outcomes derived from the model may be empirically estimated as a reduced-form hazard model.

Assume that solutions for $s_f^*(t)$ and $s_d^*(t)$ exist and are functions of the exogenous variables: $\boldsymbol{\nu}(t), \mathbf{y}(t), w_f, w_f^o(t), w_d, w_d^o(t), \mathbf{z}(t)$. After substituting the optimal policy functions into the value function (equation (2.6)), the reduced form of the fire stock distribution is

$$\begin{aligned} G(\bar{f} \mid s_f^*(t), \mathbf{z}(t), f(t), t) &= G(\bar{f} \mid \boldsymbol{\nu}(t), \mathbf{y}(t), w_f, w_f^o(t), w_d, w_d^o(t), \mathbf{z}(t), f(t), t) \\ &= G(\bar{f} \mid \mathbf{x}(t), f(t), t) \end{aligned} \quad (2.10)$$

where $\mathbf{x}(t) = [\boldsymbol{\nu}(t), \mathbf{y}(t), w_f, w_f^o(t), w_d, w_d^o(t), \mathbf{z}(t)']'$ represents all exogenous covariates.

Equations (2.7) and (2.10) state that the probability of the response effort ending in the next interval of time, conditional on the fire having persisted beyond time t , is equal to the probability that the fire stock falls below the critical value $\bar{f}$. In hazard model terminology, this conditional probability is known as the hazard rate where *hazard* refers to the probability of an event occurring in the next instant of time. In the context of wildfire, the event is the termination of the fire. As the fire progresses over time, the path of hazard rates forms the hazard function denoted

$$\begin{aligned} h(t \mid \mathbf{x}(t)) &= \int_0^t G(\bar{f} \mid \mathbf{x}(\tau), f(\tau), \tau) d\tau \\ &\equiv \lim_{\Delta t \rightarrow 0} \frac{\Pr(t \leq T < t + \Delta t \mid \mathbf{x}(t), T \geq t)}{\Delta t} \\ &= \frac{\phi(t \mid \mathbf{x}(t))}{\Psi(t \mid \mathbf{x}(t))}. \end{aligned} \quad (2.11)$$

The hazard function is equal to the density, $\phi(t \mid \mathbf{x}(t))$, over the survival function, $\Psi(t \mid \mathbf{x}(t)) = 1 - \Phi(t \mid \mathbf{x}(t))$ where $\Phi(t \mid \mathbf{x}(t)) = \int_0^t \phi(\tau \mid \mathbf{x}(\tau)) d\tau$.¹⁸ The survival function represents the probability that the fire will persist beyond a given t and is monotonically decreasing. In reference to the model of disaster response, the survival function accounts for the process by which managers accumulate information throughout the disaster.

While hazard models generally study the time until an event occurs, the cost and area of a wildfire are also valid measures of duration (Triplett, 1999; Etzioni et al., 1999; Jain and Strawderman, 2002). Because fire size and costs accumulate over the course of the fire, $A(t) = \int_0^t a(\tau) d\tau$ and $C(t) = \int_0^t c(\tau) d\tau$, I apply the same logic used to derive equation (2.11) to construct hazard functions of area and cost:¹⁹

$$h(k \mid \mathbf{x}(k)) = \frac{\phi(k \mid \mathbf{x}(k))}{\Psi(k \mid \mathbf{x}(k))} \quad \text{where } k = a, c$$

All three outcomes – duration, cost, and size – represent three perspectives on an underlying stochastic process f , which is imperfectly observed by the fire managers, and completely unaccounted for in the data. Due to the joint dependence of duration, size, and cost on the stochastic f , the outcomes are correlated random variables. I exploit this correlation in the development of the trivariate frailty model of wildfire duration, cost, and size.²⁰

I employ a parametric proportional hazard model to study the impact of covariates on duration, cost, and fire size. The term *proportional* implies that the covariates shift a parametric baseline hazard function proportionately over the support. The hazard function

¹⁸While it is instructive to think of the hazard function as a conditional probability, it is not upper bounded by one. See Kalbfleisch and Prentice (1980); Blossfeld, Hamerle, and Mayer (1989); Petersen (1995) for a technical development of the components to hazard analysis.

¹⁹One may think of cumulative size and cost as alternative measures of the wildfire's progression.

²⁰In the hazard literature, the introduction of a latent variable gives rise to a variant of hazard models called frailty models.

for each outcome $k = t, a, c$ is

$$h(k | \mathbf{x}(k)) = h_0(k)\gamma(\mathbf{x}(k)) \quad (2.12)$$

where $h_0(k)$ for $k = t, a, c$ are the baseline hazard functions, and the survival functions are

$$\Psi(k | \mathbf{x}(k)) = \Psi_0(k)^{\gamma(\mathbf{x}(k))} \quad (2.13)$$

where $\Psi_0(k)$ for $k = t, a, c$ are the baseline survival functions. Covariates are introduced through a multiplicative function, $\gamma(\mathbf{x}(k)) = \exp\{\mathbf{x}(k)\boldsymbol{\beta}_k\}$ where $k = t, a, c$. The exponential function is commonly used because the hazard function must be non-negative over the support.

Holmes, Huggett, and Westerling (2008) and Strauss, Bednar, and Mees (1989) argue that heavy-tailed distributions most accurately describe the distribution of wildfire size, among other disaster outcomes. In light of their results, I assume each outcome is distributed Weibull, which takes on a heavy tail when the shape parameter is less than one (Embrechts, Klüppelberg, and Mikosch, 1997).

I introduce a jointly distributed random component, $\boldsymbol{\varepsilon}$, correlated across equations, but constant over time, that represents unobserved heterogeneity beyond that captured in the covariates $\mathbf{x}$.²¹ The system of hazard and survival functions is

$$\begin{aligned} h(t|\mathbf{x}, \boldsymbol{\varepsilon}_t) &= h_0(t) \exp\{\mathbf{x}\boldsymbol{\beta}_t + \boldsymbol{\varepsilon}_t\} & \Psi(t|\mathbf{x}, \boldsymbol{\varepsilon}_t) &= \Psi_0(t)^{\exp\{\mathbf{x}\boldsymbol{\beta}_t + \boldsymbol{\varepsilon}_t\}} \\ h(c|\mathbf{x}, \boldsymbol{\varepsilon}_c) &= h_0(c) \exp\{\mathbf{x}\boldsymbol{\beta}_c + \boldsymbol{\varepsilon}_c\} & \Psi(c|\mathbf{x}, \boldsymbol{\varepsilon}_c) &= \Psi_0(c)^{\exp\{\mathbf{x}\boldsymbol{\beta}_c + \boldsymbol{\varepsilon}_c\}} \\ h(a|\mathbf{x}, \boldsymbol{\varepsilon}_a) &= h_0(a) \exp\{\mathbf{x}\boldsymbol{\beta}_a + \boldsymbol{\varepsilon}_a\} & \Psi(a|\mathbf{x}, \boldsymbol{\varepsilon}_a) &= \Psi_0(a)^{\exp\{\mathbf{x}\boldsymbol{\beta}_a + \boldsymbol{\varepsilon}_a\}} \end{aligned}$$

where $\boldsymbol{\varepsilon} = (\boldsymbol{\varepsilon}_t, \boldsymbol{\varepsilon}_c, \boldsymbol{\varepsilon}_a)' \sim N(0, \boldsymbol{\Omega})$ is included in the the function $\gamma(\cdot)$ in equations (2.12) and (2.13).²² The “time-varying” notation on covariates $\mathbf{x}(k)$ is now used only when necessary

²¹Wienke et al. (2005) provides a survey of frailty models and their multivariate extensions and discusses the associated estimation methodologies.

²²The restriction of $\mu = 0$ is inconsequential because any deviation from zero would be subsumed into the

to distinguish variables in an equation. The log-normal distribution²³ is chosen to describe the unobserved heterogeneity because of the heavy-tail properties as well as its explicit parameterization of the correlation in the covariance matrix $\mathbf{\Omega}$.

The joint conditional density is

$$\phi(t, c, a|\mathbf{x}, \boldsymbol{\varepsilon}) = \phi(t|\mathbf{x}, \boldsymbol{\varepsilon}_t) \phi(c|\mathbf{x}, \boldsymbol{\varepsilon}_c) \phi(a|\mathbf{x}, \boldsymbol{\varepsilon}_a), \quad (2.14)$$

where $\phi(k|\mathbf{x}, \boldsymbol{\varepsilon}_k) = h(k|\mathbf{x}, \boldsymbol{\varepsilon}_k) \cdot \Psi(k|\mathbf{x}, \boldsymbol{\varepsilon}_k) \forall k$. The unconditional joint density is obtained by integrating over $\boldsymbol{\varepsilon}$,²⁴

$$\phi(t, c, a|\mathbf{x}) = \int_{\boldsymbol{\varepsilon}} \phi(t, c, a|\mathbf{x}, \boldsymbol{\varepsilon}) \exp\{q(\boldsymbol{\varepsilon})\} d\boldsymbol{\varepsilon} \quad (2.15)$$

where

$$q(\boldsymbol{\varepsilon}) = \frac{1}{(2\pi)^{\frac{3}{2}} |\mathbf{\Omega}|^{\frac{1}{2}}} \exp \left\{ -\frac{1}{2} \boldsymbol{\varepsilon}' \mathbf{\Omega}^{-1} \boldsymbol{\varepsilon} \right\}.$$

The Likelihood function for this trivariate problem over $i = 1 \dots n$ wildfire observations is

$$L(\boldsymbol{\theta}|\mathbf{x}) = \prod_{i=1}^n \phi(t_i, c_i, a_i|\mathbf{x}_i)^{\delta_i} \Psi(t_i, c_i, a_i|\mathbf{x}_i)^{1-\delta_i} \quad (2.16)$$

where δ_i is the censoring indicator. Maximization of the full trivariate likelihood function $L(\boldsymbol{\theta}|\mathbf{x})$ in Equation 2.16, where $\boldsymbol{\theta}$ includes $\mathbf{\Omega}$, provides consistent estimates of model parameters. Estimating the duration, cost, and size hazard regressions independently is equivalent to restricting the off-diagonal elements of the covariance matrix $\mathbf{\Omega}$ to be zero. Equation 2.15 requires integration of the CDF over $\boldsymbol{\varepsilon}$. Unfortunately, a closed form solution to this problem

scale parameter of the Weibull baseline hazard which may be interpreted as the intercept analog in a linear regression.

²³Note that $\boldsymbol{\varepsilon}$ appears in the exponential covariate function which implies that the multiplicative effect on the baseline hazard and survival function is log-normal.

²⁴The use of the term “unconditional” here refers to the fact that the joint density is no longer conditional on $\boldsymbol{\varepsilon}_k$. The density, hazard, and survival functions remain conditional on $\mathbf{x}$ throughout the remainder of the analysis.

does not exist (Wienke et al., 2005).²⁵ Therefore, I apply a maximum simulated likelihood estimation (MSLE) procedure that approximates the unconditional joint density $\phi(t, c, a|\mathbf{x})$.²⁶

I program the likelihood function in Matlab (Mathworks, 2010) and use the constrained optimization interior-point algorithm to maximize the function. The algorithm uses the BFGS method to optimize the nonlinear likelihood function over the parameters $\boldsymbol{\beta}$, $\boldsymbol{\varsigma}$, and $\boldsymbol{\lambda}$ of the Weibull distribution, and the covariance matrix parameters of the frailty distribution, $\boldsymbol{\Omega}$. The algorithm converges on a solution and terminates once the gradient, the change in the function value, and the change in the norm of the estimated parameter vector reaches tolerance 10^{-4} .

2.3 Data

The data used in this analysis comes from the Incident Status Summary (ICS-209) databases (FAMWEB, 2012), the National Interagency Fire Management Integrated Database (NIFMID) (KCFast, 2012), and the 2010 U.S. Census (Census, 2012). The National Wildfire Coordination Group maintains a database that contains situational reports, filed intermittently by wildfire incident commanders throughout the suppression effort. These reports begin at the time of discovery and end when the suppression effort is complete. Each report includes data on weather, geographic, and environmental characteristics as well as assets threatened and destroyed by the fire. The wildfire data is supplemented by home value data from the 2010 U.S. Census at the Census Designated Place (CDP) level.

²⁵The parametric hazard model is chosen over the semi-parametric Cox model because the integral of the mixture distribution over the latent variable is undefined without specifying the functional form of the baseline hazard function (Liu, Wolfe, and Kalbfleisch, 2006).

²⁶See Greene (2008) for a brief overview of maximum simulated likelihood estimation.

Table 8 in the appendix provides variable names, data descriptions, and source information for all variables used in the empirical analysis. The wildfire suppression effort is considered complete when the fire is no longer growing (in terms of my notation, $a_{i\tau-1} = a_{i\tau}$).²⁷ This definition is consistent with the terminal condition, $f(T) \leq \bar{f}$, in the dynamic program. Because hazard models rely on the accumulation of time, area, and cost, consecutive reports in which the suppression cost or fire size remained constant yield no additional information to the model, and are removed from the dataset.

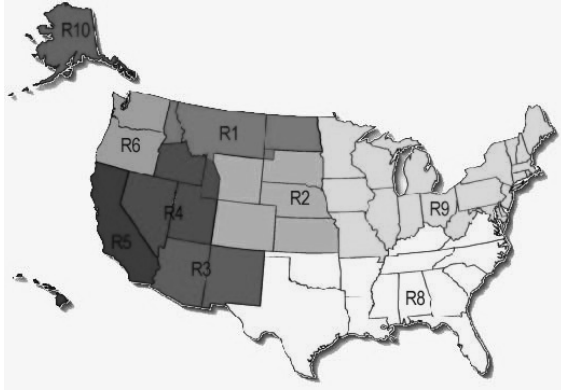
The structure of the likelihood function suggests that each fire is an independent event. However, we know that fires within a region compete for suppression resources. Therefore, we construct the variable **Resource Scarcity** as an instrument for the availability of resources during a suppression effort. For each observation, we sum the cumulative growth of all wildfires within a region, within the past five days, and subtract the mean growth of fires in that region during that month across all years. Positive values indicate that fire activity in the region is above average, and resources are likely scarce. Negative values imply that fire activity is less than expected, leaving desired resources available for dispatch. Conditional on **Resource Scarcity** the fires are assumed independent.

Suppression resources are regionally managed by Geographic Area Coordination Centers (GACC). However, the dataset contains the Forest Service region where the wildfire began. Fortunately, the GACC regions correspond to the FS regions with some exceptions as illustrated in Figure 1. The two most important exceptions are the division of California into separate GACC regions and Nevada as its own GACC. I do not believe that these discrepancies significantly affect the results.

There are two general categories of covariate: time-varying covariates, $\mathbf{x}_{i\tau} \in \mathbf{x}$, take on

²⁷Finney, Grenfell, and McHugh (2009) also consider a wildfire contained if the burned area does not increase between reports.

Figure 1: Maps of Forest Service and GACC regions. See Table 9 for FS region names.



(a) Source: U.S. Forest <http://www.fs.fed.us/contactus/regions.shtml>



(b) Source: Geographic Area Coordination Center http://gacc.nifc.gov/images/map_national.gif

different values over the course of the fire and time-invariant covariates, $\mathbf{x}_i \in \mathbf{x}$, remain constant over the duration of the fire. With the exception of weather covariates, time-varying covariates are lagged one period to avoid endogeneity (Petersen, 1995). For instance, the number of threatened residential homes reported in period $t - 1$ is considered predetermined in period t . Recall the conditionality of the hazard function on the survival function. The survival function effectively accumulates information over the course of the fire such that increases in duration (size, or cost), from one observation to another, are attributable to covariate values during that interval.²⁸ Therefore, fire growth in period t cannot influence covariate values (e.g., number of threatened residential homes) in period $t - 1$. The covariates **Threatened Structures** and **Potential Evacuation** are chosen over their confirmed counterparts (**Destroyed Structures** and **Confirmed Evacuation**) because I believe that “threatened” and “potential” reflect the incident commanders assessment of the wildfire’s current status. Therefore, any resource allocation decisions made at time t will affect future outcomes.

²⁸The survival function is qualitatively similar to the number of previous intervals variable included in Finney, Grenfell, and McHugh (2009) GLMM.

Table 9 in the appendix presents summary statistics of the covariates used in this analysis. The dataset contains 10,321 observations on 3,829 fires. Means and standard deviations of time-varying covariates $\mathbf{x}_{i\tau}$ are based on all observations (10,321) while the statistics of time-invariant covariates $\mathbf{x}_i$ and the dependent variables duration, cost, and size are based on one record per fire (3,829).

2.4 Results

Table 10 in the appendix contains the parameter estimates β_k and standard errors for duration, cost, and area, as well as the ancillary Weibull distribution parameters. In order to provide context for the coefficient estimates, I first discuss the ancillary parameters of the Weibull distribution that determine the shape of the baseline hazard function. The baseline is defined as the hazard function where all of the covariates are null. Because some continuous covariates, such as temperature, rarely take a null value, I also present the hazard function with the continuous covariates evaluated at their median value (categorical variables are left as their null values). The environmental and wildfire characteristics represented by the baseline and median scenarios are described in Table 11 in the appendix.

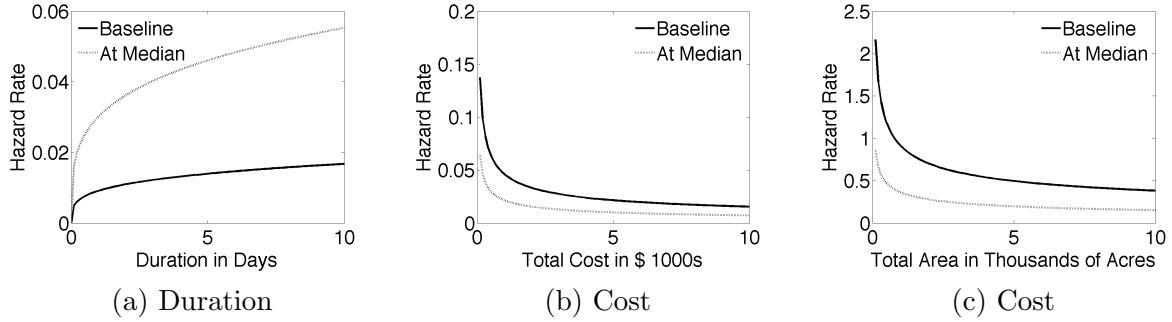
The baseline Weibull hazard function $h_0(k) = \lambda_k \varsigma_k (\lambda_k k)^{\varsigma_k - 1}$ for $k = t, c, a$ is parameterized by a shape (ς_k) and scale (λ_k) parameter.²⁹ The baseline hazard functions for duration, cost, and area are presented in Figure 2.³⁰

The hazard function for duration is increasing over time (ς_t (shape) = 1.25), which implies that as the duration of a wildfire grows, the probability of containment (conditional on no containment to date) rises. The decreasing hazard functions of suppression cost ($\varsigma_c = 0.53$)

²⁹Because the covariates multiplicatively affect the baseline hazard function through the proportionality factor, I can subsume λ_k into the exponential function as $\gamma(\mathbf{x}) = e^{\beta_0 + \mathbf{x}\beta_k}$ where $\beta_0 = \varsigma_k \log(\lambda_k)$. In this form, the scale parameter is analogous to the intercept in a linear regression.

³⁰It is important to note that these estimates are not intended to represent the natural, unsuppressed growth of a wildfire. The model should be interpreted as the reduced form of an underlying structural model, with suppression effort implicit in the outcomes.

Figure 2: Hazard functions of duration, cost, and area: baseline and at median values of covariates.



and fire size ($\varsigma_a = 0.63$) imply that as wildfires become more expensive and large in area, the instantaneous probability of containment declines.³¹ These results are consistent with those of Holmes, Huggett, and Westerling (2008) and Strauss, Bednar, and Mees (1989) who find that while most fires are contained when the fire is small, some fires grow excessively large and become very difficult to suppress.

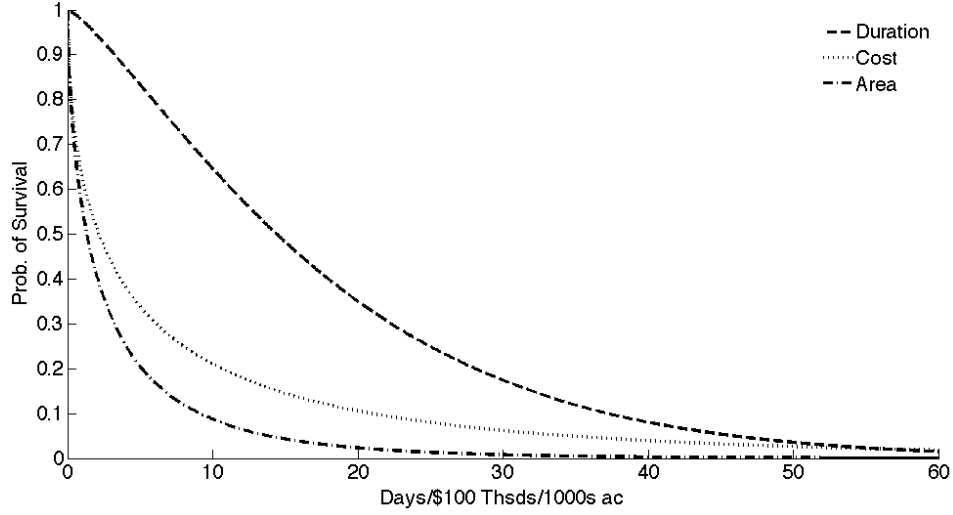
The survival function $\Psi(k|\mathbf{x}) = \exp\{-(\lambda_k k)^{\varsigma_k} \cdot \exp\{\mathbf{x}\boldsymbol{\beta}_k\}\}$, as specified in equation (2.13), represents the probability that a fire persists beyond a given duration (cost, or size). At the point of ignition, the fire is certain to persist until the next instant of time ($\Psi(0) = 1$). As duration (cost, or size) grows, the probability of persistence, or fire survival, falls. Figure 3 depicts the survival functions of all three models, evaluated at the median covariate values.³²

The bottom section of the Table 10 contains the elements of the Cholesky triangle $\mathbf{L}$ which satisfies the equation $\boldsymbol{\Omega} = \mathbf{L}\mathbf{L}'$. The covariance matrix of the normally distributed

³¹Note that the cumulative hazard rate is always increasing, even when the instantaneous hazard rate is decreasing over the domain. In other words, the probability of a fire growing larger than 100 thousand acres is less than the probability of a fire growing larger than 10 thousand acres despite the smaller hazard rate at 100 thousand acres.

³²Recall that the survival function is one minus the probability of containment, $\Psi(t | \mathbf{x}(t)) = 1 - \Phi(t | \mathbf{x}(t))$. Figure 3 is the complement to Figure 2 in Finney, Grenfell, and McHugh (2009).

Figure 3: Survival functions evaluated at median covariate values



unobserved heterogeneity, ϵ , and the associated correlation matrix are

$$\hat{\Omega} = \begin{bmatrix} \hat{\sigma}_{tt} & \hat{\sigma}_{tc} & \hat{\sigma}_{ta} \\ \hat{\sigma}_{tc} & \hat{\sigma}_{cc} & \hat{\sigma}_{ca} \\ \hat{\sigma}_{ta} & \hat{\sigma}_{ca} & \hat{\sigma}_{aa} \end{bmatrix} = \begin{bmatrix} 0.6813 & 0.6521 & 0.7687 \\ 0.6521 & 0.6282 & 0.7409 \\ 0.7687 & 0.7409 & 0.8740 \end{bmatrix}$$

$$\hat{\mathbf{P}} = \begin{bmatrix} 1 & \hat{\rho}_{tc} & \hat{\rho}_{ta} \\ \hat{\rho}_{tc} & 1 & \hat{\rho}_{ca} \\ \hat{\rho}_{ta} & \hat{\rho}_{ca} & 1 \end{bmatrix} = \begin{bmatrix} 1.0000 & 0.9992 & 0.9990 \\ 0.9992 & 1.0000 & 1.0000 \\ 0.9990 & 1.0000 & 1.0000 \end{bmatrix}.$$

While not all of the estimates of $\mathbf{L}$ are statistically different from zero, a likelihood ratio test rejects the joint hypothesis that $\sigma_{ij} = 0$ for all $i, j = t, c, a$ with a $LR = 898.32 \sim \chi_6^2$ (p-value= < 0.0001).³³ The off-diagonal elements of the correlation matrix are above 0.99, which indicates that the outcomes, duration, cost, and area covary closely. While such close covariation is expected, this result underscores the importance of jointly modeling duration, cost, and area.

³³I also conduct a LR test of uncorrelated heterogeneity with a null hypothesis of $\sigma_{ij} = 0$ for all $i \neq j$. $LR = 705.04 \sim \chi_3^2$ (p-value= < 0.0001).

Table 1: Selected results. Percent effect of a change in covariate on expected duration, cost, and size

	Duration	Cost	Area
Threatened Residential (100s)	8.56**	22.23***	26.02***
Threatened OutBuildings (100s)	3.17	16.67**	35.03***
Potential Evacuation	120.89***	330.42***	401.83***
Threatened Commercial (100s)	-28.95***	-15.99	14.58
Resource Scarcity (100k acres)	2.58	3.81*	13.42***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Hypothesis tests are based on underlying parameter estimates

Propositions 1, 2, and 3 are the foundation of three hypotheses: when the number of threatened assets rise, wildfire management teams divert resources from suppression toward protection of threatened assets, which causes 1) longer, 2) larger, and 3) more costly expected wildfires. Table 1 contains a subset of the results that support these hypotheses. Table 10 in the appendix contains the full set of results. The parameter estimates in Table 1 are transformed to show the percent effect of a one unit change in a covariate on the ex ante expected duration, size, and cost of a fire.

The results indicate that the expected duration, cost and size of a wildfire are affected by an increase in the number of threatened assets. When the number of **Threatened Residential** homes increases by 100, the expected cost and size of a fire rise by 22% and 26%, respectively. These results contrast with those of Donovan, Noordijk, and Radeloff (2004) who find that threatened homes have no statistically significant effect on wildfire cost.³⁴ Similarly, an increase of 100 **Threatened Outbuildings** raises the expected cost and size of a fire by 16.6% and 35%, respectively.³⁵ The impact of threatened resources on the expected wildfire cost suggest that at least one of the conditions in proposition 3 is met. I attribute these results to a reallocation of response resource away from suppression towards

³⁴Note that Donovan, Noordijk, and Radeloff (2004) treat wildfire size as an exogenous variable in a linear regression of total suppression costs, whereas the model considers suppression costs an endogenous outcome.

³⁵The magnitude of the estimates for **Threatened Residential** and **Threatened Outbuildings** are not statistically different from each other.

protection.

Potential Evacuation is a subjective measure of the suppression management team's level of concern regarding the safety of a community. **Potential Evacuation** increases the expected duration by 121%, the expected costs by 330%, and the expected size by 401%. In addition to protecting threatened residences, resources may be used to prepare and manage evacuations, leaving fewer resources available for suppression.

The estimates in the duration and cost equations associated with **Threatened Commercial** are not consistent with hypotheses 1) and 2). An increase of 100 **Threatened Commercial** reduce the expected duration by 29% and reduces the expected costs by 16% (not statistically significant). However, the expected size increases by 15% when the number of **Threatened Commercial** rises by 100. While the duration and cost results do not appear to be consistent with the theory, the management team's perception of insurance may impact resource allocation decisions. Suppose that fire managers believed commercial structures are fully insured against fire damage as opposed to residential structures and outbuildings whose non-market value cannot be fully insured (Yoder, 2010). The management team may treat commercial structures as a low value asset and continue suppression rather than shifting suppression effort toward protecting specific assets.

The ability of suppression management teams to optimally allocate resources to a specific fire is contingent on the availability of the desired resources, which depends on fire activity in the region. The cost function in the theoretical model given by equation (2.2) includes an opportunity cost w_i^o for $i = f, d$ meant to capture the availability of resources. I include the variable **Resource Scarcity** as an instrument for w_i^o . I find that when fire activity in the region increases by 100,000 acres within a span of five days: the expected duration increases by 2.5% (not statistically significant), the expected cost increases by 4%, and the expected size increases by 13%. As the opportunity cost of suppression resources rises, the management team may not apply sufficient suppression effort leading to larger and more

costly expected fire outcomes.

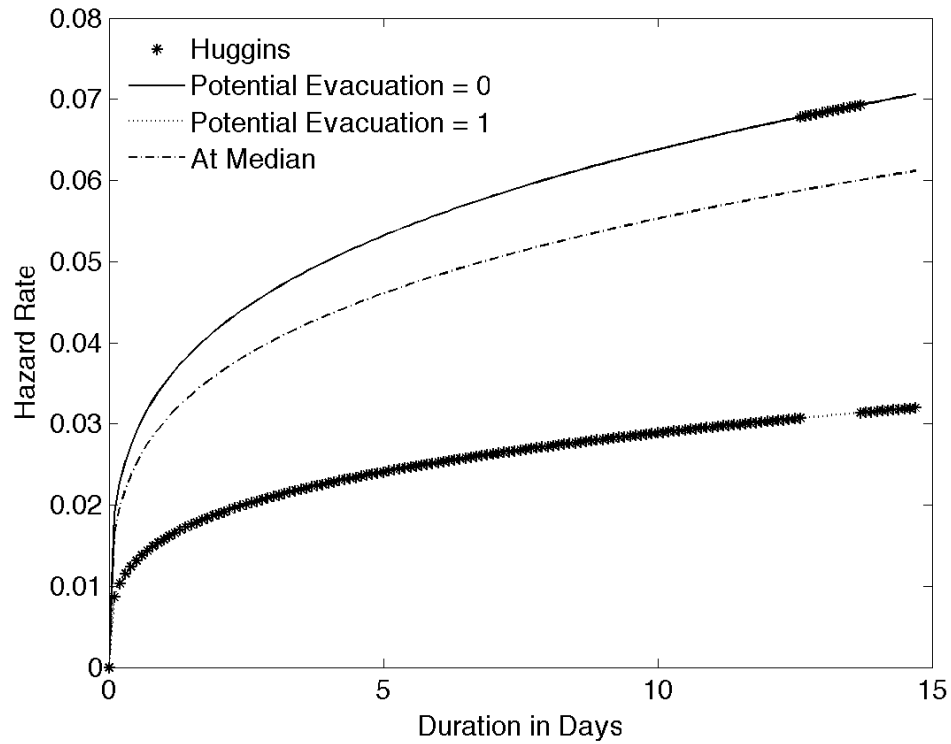
The covariate coefficients provide information about the impact of a covariate at any given point in time. However, conditions change over the course of the wildfire. These changes cause the hazard function to “jump” from the hazard rate reflecting the previous covariate state to that of the new state. Therefore, the hazard function is not continuous over the course of a particular wildfire. The survival function, on the other hand, is continuous and provides an intuitive representation of the wildfire’s progression over time.

Figure 4 contains the hazard and survival functions of the Huggins fire, a wildfire in Curry County, Oregon that started in July 2005. In order to illustrate the effect of a time-varying covariate on the hazard rate and survival function, I fix all covariates, except for `potential evacuation`, to their within-fire median values. The Huggins wildfire lasted 40 days, however, the transition between covariate values is clearer when the duration axis is truncated.

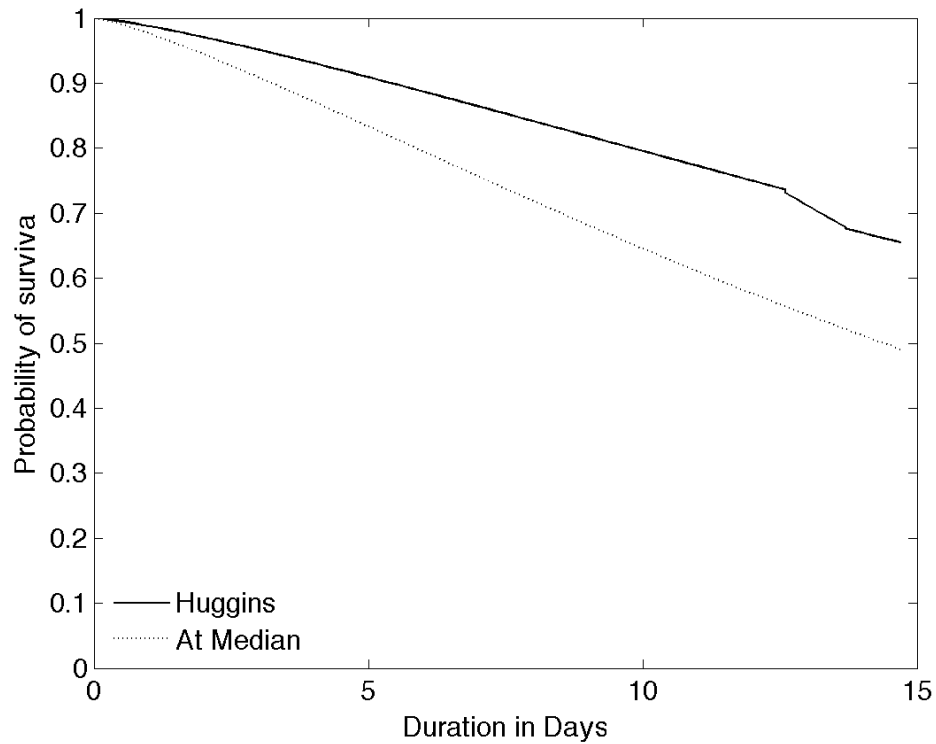
Figure 4a displays four hazard functions: 1) at the population median covariate levels, 2) at `Potential Evacuation = 0` (with other covariate fixed to their within-fire median), 3) at `Potential Evacuation = 1`, and 4) the hazard function based on the Huggins fire data. The initial duration hazard rate corresponds to `Potential Evacuation = 1` that persists for 12.5 days.³⁶ Given that `potential evacuation` reduces the hazard of containment ($\beta_{\text{pot evac}} = -0.792$ from table 10), the Huggins fire hazard function lies below the median population hazard function. The jump in the Huggins hazard function represents the instantaneous transition to a new state corresponding to a new ICS-209 report. During the interval 12.5 to 13.7 days, the potential for evacuation is removed, and the hazard of containment jumps to the hazard function associated with `Potential Evacuation = 0`. After day 13, the potential for evacuation was reinstated, and the hazard of containment fell once again. I

³⁶Note that the dataset contains numerous reports within the 12 day interval in which other time-varying covariates change. However, all other covariate are fixed at their median level to illustrate the marginal effects of a change in a time-varying covariate during a fire.

Figure 4: Hazard and survival function of Oregon wildfire experiencing potential evacuation.



(a) Hazard function



(b) Survival Function

attribute these large shifts in the probability of containment to shifts between suppression and protection strategies in response to threatened assets.

Figure 4b displays the population median survival function, and the Huggins fire survival function, which represents the cumulative effects of changing **potential evacuation** over the course of the fire. During the first 12.5 days, the probability of the fire persisting another day gradually declines due to the existing potential for evacuation. Midway through day 12, the potential for evacuation is removed and the slope of the survival function decreases. The kink in the survival function reflects the instantaneous transition to the higher hazard rate depicted in figure 4a. Once the potential for evacuation is reinstated, the slope of the survival function rises to a level consistent with that during the interval from 0 to 12.5 days. However, the curve has shifted down, due to the interval of increased containment probability, reflecting the cumulative nature of the survival function. I consider the cumulative aspect of the survival function an important feature of this hazard model approach because it approximates the wildfire manager’s accumulation of information over the course of the fire.

2.5 Conclusion

I have proposed a model of disaster response applied to wildfire in which managers face tradeoffs between suppression and protection while attempting to minimize costs and damage. I hypothesize that an increase in the number of threatened assets causes managers to shift resources from suppression toward asset protection. The model predicts that the diversion of resources causes the expected duration, cost, and size of the fire to rise.

The model of disaster response, and the focus on disaster outcomes, lends itself to an empirical duration model. I derive the foundations of a duration model from the dynamic model of disaster response and estimate a trivariate hazard model. The results support the predictions of the theory: an increase in the number of threatened assets increases the

expected duration, cost, and size of the fire. In addition, I find that the trivariate hazard model with correlated unobserved heterogeneity outperforms the model with independent unobserved heterogeneity, which outperforms the model without unobserved heterogeneity. This result underscores the importance of jointly estimating disaster outcomes; specifically, modeling wildfire size and cost as jointly determined outcomes.

The results of this analysis imply that the growing wildland urban interface has, and will continue to influence wildfire size and cost. As more structures are built in zones with high risk of fire, the results imply that fires are expected to last longer, grow larger, and cost more as structures are threatened during wildfire. Given the emphasis on structure protection, policies that limit, or discourage, the expansion of wildland urban interface may lead to smaller fires and lower federal annual expenditures on fighting wildland fire. The recent rural homeowners fee imposed by the state of California charges those with homes in the wildland urban interface and annual fee of \$150 to offset the cost of structure protection.

The modeling framework proposed in this analysis provides ex-ante and ex-post information to fire-fighting agencies at all levels. The Huggins fire example demonstrates how the results of this model may be used by wildfire managers to understand the probabilistic behavior of wildfire given the limited information they accrue throughout the response effort. Results from the hazard model may be integrated with existing management tools such as the Wildland Fire Decision Support System, used to project fire behavior and future resource needs (Service, 2011). Furthermore, analyzing the survival function after the response effort is complete may provide information that would help agencies such as the U.S. Forest Service and Bureau of Land Management assess their management and resource prepositioning strategies.

Chapter 3

A Model of Wildfire Response Resource Allocation

3.1 Introduction

Wildfire is a dynamic and stochastic physical process that alters ecosystems and destroys natural and manmade assets. As such, costly suppression activity is undertaken to manage wildfire growth and protect threatened assets. Fire managers, operating in an uncertain environment, accumulate information and develop, implement and update management plans. When multiple wildfires are burning within a region, a regional command unit allocates response resources between fires constraining the operations of an individual fire manager.¹ The incentives of an individual fire manager throughout the course of a fire are complex and poorly understood (Calkin et al., 2013).

The recent escalation of wildfire management costs has focused the attention of policy-makers and researchers on the factors that contribute to large expensive wildfires. This question depends on the micro-level behavior of individual wildfire managers, as well as regional command units, during a response effort. A clear understanding of wildfire management incentives is a prerequisite to analyzing the factors that contribute to growing wildfire costs.

The objectives of this study are twofold: develop a bioeconomic model of wildfire response that explicitly incorporates the interaction between fire managers and regional command

¹The term fire manager describes the individual decision maker “on the ground” at any single fire. This individual, or group of individuals depending on the size and complexity of the fire, is called the incident commander or incident management team. The term regional command unit refers to Geographic Area Coordination Centers (GACC) who coordinate the distribution of response resources within a geographically defined area.

units; estimate a theoretically consistent two-stage econometric model of wildfire cost, size, and structure damage where the first stage is a set of response resource allocation equations. The theoretical model motivates a hypothesis for how an increase in threatened residential structures leads to larger and more expensive fires. The econometric model provides support for this hypothesis and offers new insights into the relative productivity of response resources throughout the course of a wildfire.

Since Sparhawk (1925), theoretical models of wildfire response management have focused on the cost plus net loss framework for a given fire or fire season (Bratten, 1970; Mees and Strauss, 1992; Donovan and Rideout, 2003; Donovan and Brown, 2005). However, few studies model the complexity of managing multiple wildfires simultaneously; notable exceptions include Kirsch and Rideout (2005) and Petrovic, Alderson, and Carlson (2012). Of these studies, none have explicitly modeled, theoretically or empirically, the interaction between individual fire managers and the regional command unit. By explicitly modeling this interaction, I show how the fire manager conveys his or her marginal value of a resource to the regional command unit. Furthermore, the model yields a set of structural equations from which I derive a set of estimable reduced-form response resource allocation equations. Estimates from the response resource allocation equations are used to generate instruments for endogenous response resources in a set of second-stage regressions on wildfire cost, size and damage.

Most empirical studies of wildfire outcomes rely on data aggregated over a fire, or even an entire fire season (Liang et al., 2008; Abt, Prestemon, and Gebert, 2009; Yoder and Gebert, 2012).² The few studies that have used micro-level panel data to study wildfire outcomes estimate reduced-form models from which the estimates contain both direct and indirect

²Another class of studies construct models of wildfire response, and simulate response strategies (Fried, Gilles, and Spero, 2006; Haight and Fried, 2007; Petrovic, Alderson, and Carlson, 2012). While the policy implications of these studies are comparable to empirical studies based on data, the method of analysis is not.

impacts (Donovan, Noordijk, and Radeloff, 2004; Finney, Grenfell, and McHugh, 2009; Gude et al., 2013). Such models offer insights into the factors that contribute to wildfire cost and size, but are unable to identify a mechanism that leads to the observed wildfire outcomes. In contrast, this study utilizes a dynamic panel dataset that covers the entire U.S. from 2001 to 2010 and includes data on response resource allocation. Data on response resources allows us to test the mechanism proposed to explain how more threatened homes lead to larger and more expensive fires.

Dynamic panel models have been used to study a variety of economic phenomenon from employment (Arellano and Bond, 1991) to growth and development (Dietz, Neumayer, and De Soysa, 2007), but have not yet been applied to resource allocation problems in the context of disaster response. Wildfire response is driven by the evolution of the wildfire, which is inherently a dynamic process. The Arellano-Bond systems estimator, proposed by Blundell and Bond (1998), accounts for a dynamic process with a lagged dependent variable and accommodates endogenous regressors. The estimator overcomes dynamic panel bias by instrumenting the lagged dependent variable (and any endogenous regressors) with further lags established to be exogenous by the specification test proposed in Arellano and Bond (1991). I use the Arellano-Bond systems estimator to consistently estimate the first-stage resource allocation equations derived from the proposed model of wildfire response.

In a second stage, I estimate a set of shared frailty hazard models of wildfire cost and size (as in chapter 2), and a zero-inflated negative binomial model of number of residential structures damaged and destroyed. In each of these second-stage models, I instrument endogenous response effort with predicted values from the first-stage models of response resource allocation. This study extends the analysis in chapter 2 by 1) identifying the channels through which environmental factors and threatened resources affect wildfire cost and size, and 2) estimating the effectiveness of response effort in mitigating damage to residential structures.

The results suggest that wildfires in which residential structures are threatened receive more firefighter crews and bulldozers and fewer engines. Second stage results then indicate that firefighter crews and bulldozers reduce structure damage, but lead to larger more expensive fires. In contrast, highly trained firefighter crews and engines reduce fire size and only marginally increase fire cost, but do not significantly reduce structure damage. Together these results provide support for the hypothesis that threatened homes cause fire managers to divert response resources from suppression toward protection, which allows the fire to grow larger, and ultimately cost more to manage.

The remainder of the paper is outlined as follows. Section 3.2 develops a model of wildfire response to explicitly characterize the interaction between individual fire managers and a regional command unit. Section 3.3 describes the data and empirical models used in this analysis. Section 3.4 presents the results of the response resource allocation equations (first stage) and the hazard and count models of wildfire cost, size, and damage to structures (second stage). Section 3.5 discusses the policy implications and concludes.

3.2 Model

Consider an individual fire manager that allocates response resources within a fire, subject to a set of resource constraints determined by the regional command unit. Individual fire managers convey all relevant information about the marginal value of response resources to the regional command unit. The regional command unit aggregates this information and allocates a finite set of response resources to each fire such that the marginal value of an additional resource is equal across all simultaneously burning fires.

I model the wildfire as a stochastic process that evolves over time and may lead to economic damage. While weather and other environmental characteristics affect fire growth, feedback loops exist between human intervention and the growth of the fire. For any single

wildfire manager with a constrained number of response resources, there exists an intertemporal tradeoff between protection of currently threatened assets and suppression of fire growth. Sections 3.2.1 and 3.2.2 describe the individual fire manager’s and regional command unit’s problems, respectively.

3.2.1 Wildfire Manager

The fire manager faces a tradeoff between total fire costs and damage. Fire managers benefit by applying available response resources to mitigate damage to threatened assets, but face political pressure and employment consequences if costly resources are found to have exceeded reasonable limits. The fire manager’s loss function is

$$\ell_t(d_t, c_t),$$

where ℓ_t is the loss function and is increasing in both damages, d_t , and costs, c_t , at any point in time t .³⁴ The cost of response at time t is

$$c_t = \mathbf{y}_t' \mathbf{w}_t,$$

where $\mathbf{y}_t$ is the $(J \times 1)$ vector of response resources and $\mathbf{w}_t$ is the $(J \times 1)$ vector of corresponding wages. I classify response in terms of suppression and protection, where suppression mitigates fire growth and protection mitigates damage to currently threatened assets. All

³Donovan and Brown (2005) argue that wildfire managers are not subject to a budget constraint, but rather face disincentives for grossly exceeding reasonable levels of expenditure. Calkin et al. (2013) also acknowledge the lack of a true budget constraint in a choice experiment study of wildfire manager incentives.

⁴This general specification of the objective function accounts for several important features of wildfire management not present in the often used linear cost plus loss specification. Expenditure on response effort assigned to protect a specific structure or structures may exceed the value of the structure receiving protection (Troyer et al., 2003; Calkin et al., 2005; Calkin et al., 2013), which suggests that wildfire managers place unequal weights on costs and damage.

resources are assigned to either suppression or protection, $\mathbf{y}_t = \mathbf{y}_t^s + \mathbf{y}_t^p$.⁵ Wildfire damage at time t is given by

$$d_t = d(\mathbf{y}_t^p; \mathbf{x}_t, \mathbf{v}_t(\boldsymbol{\delta}, a_t(f_t))), \quad (3.1)$$

where $\mathbf{y}_t^p$ is a vector of response resources devoted to asset protection, $\mathbf{x}_t$ is a vector of exogenous environmental and geographic characteristics, $\mathbf{v}_t(\boldsymbol{\delta}, a_t)$ is a vector of threatened asset values that depends on asset density, δ , and fire growth at time t , $a_t(f_t)$, which in turn depends on the energy stock of the fire at time t .⁶ Damage is decreasing in protection resources, and increasing in the number of threatened assets, which is increasing in fire growth.⁷ Environmental characteristics may facilitate or hinder the productivity of response resources. Difficult terrain may severely limit the productivity of engines and dozers, while precipitation may increase the productivity of fire crews (Hirsch and Martell, 1996; Plucinski et al., 2012).

The stock of energy grows according to an equation of motion,

$$f_{t+1} = f_t + g_t(\mathbf{y}_t^s; \mathbf{x}_t) + \varepsilon_t, \quad (3.2)$$

⁵Protection and suppression effort may also be thought of as direct and indirect strategies for mitigating damage to assets. Where direct effort is necessary to mitigate damage likely to occur within the next planning period, indirect effort mitigates expected future damage beyond the next planning period. Note that the use of direct and indirect attack in this context do not correspond to the firefighting terms direct- and indirect-attack.

⁶The vector of threatened asset values may include residential and other private structures, watersheds, harvestable timber, and wildlife habitat. I focus on residential structures because I have data on number of threatened residential structures and the county median home price over the course of a fire.

⁷A particular functional form that satisfies the assumptions of equation (3.1) is

$$d_t = \left(\sum_{k=1}^K \frac{\omega_{kt} v_{kt}(\delta_{kt}, a_t)}{\sum_{j=1}^J \rho_{jk}(\mathbf{x}_t) y_{jkt}^p} \right),$$

where ω_{kt} is the subjective weight the fire manager places on asset k , $\rho_{jk}(\mathbf{x}_t)$ is the productivity of resource j at protecting asset k as a function of environmental factors, and $y_{jkt}^p \in \mathbf{y}_t^p$, $v_{kt} \in \mathbf{v}_t$, and a_t are as defined in text.

where $\mathbf{y}_t^s$ is the vector of suppression resources, $\mathbf{x}_t$ is a vector of exogenous environmental characteristics, and $g_t(\cdot)$ is growth function. The stock of energy is decreasing in all elements of $\mathbf{y}_t$ and may be increasing or decreasing in $\mathbf{x}_t$. High windspeed may promote fire growth, while higher levels of humidity may inhibit fire growth. The stock of energy is unobserved by the researcher and is therefore treated as a random variable with a disturbance ε_t . The response effort ends when the stock of energy falls below some exogenous threshold, which I normalize to zero for convenience, $f_T = 0$.⁸

The fire manager allocates response resources subject to a set of resource constraints imposed by the regional command unit. At any time t the fire manager faces the following J constraints in vector form,

$$\bar{\mathbf{y}}_t \geq \mathbf{y}_t^s + \mathbf{y}_t^p,$$

where $\bar{\mathbf{y}}_t$ is a vector of J resources committed to the fire by the regional command unit.⁹ This allocation is exogenous at time t because the regional command unit commits these resources at $t - 1$. The resource constraint (and the associated Lagrange multiplier in the constrained optimization problem) serves as the point of connection between the individual fire manager and the regional command unit.

Upon discovery of a fire, a fire manager learns the initial stock of energy, f_0 , and develops a strategy, $\{\mathbf{y}_t^p, \mathbf{y}_t^s\}_{t=0}^T$, to solve

$$\begin{aligned} \min_{\{\mathbf{y}_t^p, \mathbf{y}_t^s\}} \quad & \sum_{t=0}^T E_t[\ell_t(\mathbf{y}_t' \mathbf{w}_t, d_t)] \\ \text{s.t.} \quad & \bar{\mathbf{y}}_t \geq \mathbf{y}_t^s + \mathbf{y}_t^p \\ & f_{t+1} = f_t + g_t(\mathbf{y}_t^s; \mathbf{x}_t) + \varepsilon_t \end{aligned} \tag{3.3}$$

⁸This terminal condition is similar to the containment constraint defined in Donovan and Rideout (2003).

⁹This constraint is equivalent to the resource constraint in the linear programming model of wildfire response resource allocation Bratten (1970).

$$f_t, \bar{\mathbf{y}}_t, \mathbf{y}_t^s, \mathbf{y}_t^p \geq 0 \quad \forall t$$

$$f_T = 0,$$

where d_t is defined in equation (3.1).¹⁰ The expected duration, T , is implicitly determined by the path of $\{\mathbf{y}_t^p, \mathbf{y}_t^s\}_{t=0}^T$ and the terminal condition $f_T = 0$. The structure of this problem reflects a forward-looking rational fire manager that formulates a response policy over the planning horizon. I assume that the total resources available to the fire manager are committed to the fire by the regional commander in $t - 1$, which implies that they are exogenous to the fire manager in each period t . Over the course of the fire, the manager accumulates information and resolves his optimization problem at every period t .¹¹

After substituting equation (3.2) into equation (3.1), the first order conditions of the fire manager's minimization problem are

$$[Protection] \quad E_t \left[\frac{\partial \ell_t}{\partial \mathbf{c}_t} \mathbf{w}_t + \frac{\partial \ell_t}{\partial d_t} \frac{\partial d_t}{\partial \mathbf{y}_t^p} - \boldsymbol{\lambda}_t \right] = \mathbf{0} \quad \forall t \quad (3.4)$$

$$[Suppression] \quad E_t \left[\frac{\partial \ell_t}{\partial \mathbf{c}_t} \mathbf{w}_t + \frac{\partial \ell_{t+1}}{\partial d_{t+1}} \frac{\partial d_{t+1}}{\partial g_t} \frac{\partial g_t}{\partial \mathbf{y}_t^s} - \boldsymbol{\lambda}_t \right] = \mathbf{0} \quad \forall t \quad (3.5)$$

$$[Constraints] \quad \bar{\mathbf{y}}_t - \mathbf{y}_t^p - \mathbf{y}_t^s \geq \mathbf{0} \quad \forall t$$

$$\lambda_{jt} [\bar{y}_{jt} - y_{jt}^s - y_{jt}^p] = 0 \quad \forall j, t$$

$$\lambda_{jt} \geq 0 \quad \forall j, t.$$

Each vector equation is of dimension $(J \times 1)$. Equations (3.4) and (3.5) imply that a fire manager applies response resources to equate the marginal losses across both suppression

¹⁰While this model captures the incentives that lead to costly response effort, it also can represent the case in which few or no assets are at risk and the optimal policy is little or no response.

¹¹This formulation is consistent with the actual behavior of fire managers on the ground. In fact, the data used to estimate the empirical resource allocation equations is based on reports by fire managers when an update to the response policy is filed.

and protection. The marginal benefit of suppression is the reduction of future threatened assets which implies lower expected future costs and damages. The marginal benefit of protection is the mitigation of damage to currently threatened assets. The marginal cost of protection (suppression) include the marginal “disutility” of incurring higher costs and the opportunity cost (λ) of using the resource to provide suppression (protection) effort. The system of equations, initial, and terminal conditions implicitly define $\{\hat{\mathbf{y}}_t^s, \hat{\mathbf{y}}_t^p, \hat{\boldsymbol{\lambda}}_t\}_{t=0}^T$.

3.2.2 Regional Command Unit

The federal contract for securing a resource states that the award is based on the “best value” conditional on meeting a minimum set of requirements (NIFC, 2011). This notion of “best value” refers to the individual fire managers marginal benefit of receiving an additional resource. Individual fire managers communicate their need for response resources to the regional command unit through the shadow price λ_{ji} for each resource j and fire i . Once resources are committed to a fire, they remain committed for the entire day, after which they may be reassigned to another fire.¹² While tactics and strategies may vary idiosyncratically across individual fire managers, their primary objectives remain consistent. The regional command unit chooses I sets of J resources to minimize the sum of expected losses across all wildfires I burning at time t ,

$$\begin{aligned} \min_{\bar{\mathbf{y}}_{it}} \quad & \sum_{i=1}^I \ell_{it}(\bar{\mathbf{y}}_{it}) \quad \forall \quad t \\ \text{s.t.} \quad & \bar{\bar{\mathbf{y}}}_t \geq \sum_{i=1}^I \bar{\mathbf{y}}_{it}, \end{aligned} \tag{3.6}$$

where $\bar{\bar{\mathbf{y}}}$ denotes the constraint on resources available to the region at any given point in time, and ℓ is defined in equation (3.3). Wildfires begin and end throughout the year, so

¹²This assumption may be strong for aircraft given their mobility.

the regional command unit repeatedly solves this static minimization problem at every point in time t . However, the model remains dynamic because each fire manager's shadow price, λ_{it} , is based on the decisions of a forward-looking agent.¹³ The first-order conditions of the regional command unit's problem are

$$\begin{aligned}
 \frac{\partial \ell_{it}(\bar{\mathbf{y}}_{it})}{\partial \bar{\mathbf{y}}_{it}} &= \boldsymbol{\mu}_t \quad \forall i, t \\
 \bar{\bar{\mathbf{y}}}_t - \sum_{i=1}^I \bar{\mathbf{y}}_{it} &\geq \mathbf{0} \\
 \mu_{jt} \left[\bar{\bar{y}}_{jt} - \sum_{i=1}^I \bar{y}_{ijt} \right] &= 0 \quad \forall j \\
 \mu_{jt} &\geq 0,
 \end{aligned} \tag{3.7}$$

where $\boldsymbol{\mu}_t$ is a $(J \times 1)$ vector of shadow prices corresponding to each resource type. Equation (3.7) implies that in equilibrium, the marginal benefit of an additional resource j is equal across all fires. By definition, the regional command unit's marginal benefit of committing resource j to fire i is equal to fire manager i 's shadow price of the resource, i.e., $\frac{\partial \ell_i}{\partial \bar{y}_{ij}} = \lambda_{ij}$.¹⁴ However, the regional command unit allocates a finite set of resources and recognizes the cost of committing resource j to fire i in terms of the losses expected on fire $n \neq i$. Therefore, fire n 's shadow price of resource j is inversely related to the number of resources committed to fire i .

¹³In practice, another source of uncertainty arises from the stochastic nature of wildfire ignitions. I abstract from this complication in the theoretical model because incorporating it would increase the complexity of the model and provide little substantive information.

¹⁴The individual fire manager's Lagrangian function amounts to adding $\lambda'_t(\bar{\mathbf{y}}_t - \mathbf{y}_t^p - \mathbf{y}_t^s)$ to the objective function

$$L \equiv \sum_{t=0}^T \ell_t(\mathbf{y}_t^p, \mathbf{y}_t^s) + \lambda'_t(\bar{\mathbf{y}}_t - \mathbf{y}_t^p - \mathbf{y}_t^s) = \sum_{t=0}^T \ell_t(\mathbf{y}_t^p, \mathbf{y}_t^s)$$

Differentiating L with respect to the constraint yields the desired equality

$$\frac{\partial L}{\partial \bar{\mathbf{y}}_t} \equiv \frac{\partial \ell_t(\cdot)}{\partial \bar{\mathbf{y}}_t} = \boldsymbol{\lambda}_t \quad \forall t$$

Figure 5: Regional command unit's problem.

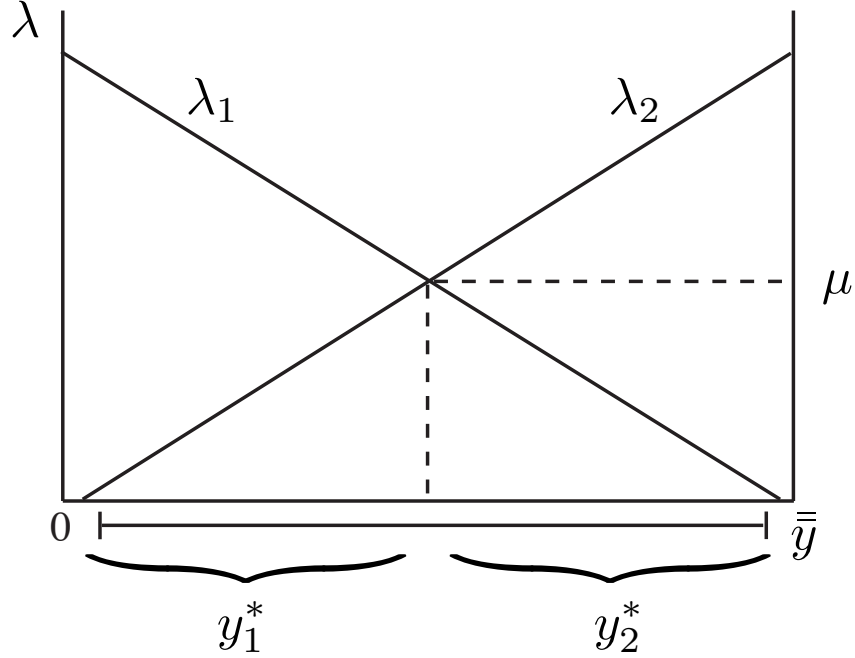


Figure 5 illustrates the regional command unit's problem of allocating a finite set of one resource type, $\bar{y}$, across two fires. Fire 1's marginal benefit of resources is decreasing in the number of resources it receives while fire 2's marginal benefit is increasing along the same dimension. The efficient allocation of $\bar{y}$ occurs at $\mu = \lambda_1 = \lambda_2$. If the total available number of resources in a region increased, the x-axis would expand, possibly to the point where λ_1 and λ_2 no longer intersect in which case, more resources are available than requested and the regional command unit's constraint would not bind $\mu = 0$. If, in contrast, a single fire requested more resources than available, $\mu = \lambda_1$ at the vertical intercept.

Equation (3.7) implies that $\lambda_{ijt} = \lambda_{-ijt} = \mu_{jt}$ for all i, j and t and forms the basis for the set of reduced-form response resource allocation equations. The solution to the individual fire manager's optimization problem implies that the shadow price, λ_{ijt} , is a function of expected outcomes at time t .

$$\lambda_{ijt} = \lambda(\bar{y}_{ijt}; w_{ijt}, \mathbf{v}_{it}(a_{it}), \mathbf{x}_{it}) \quad \forall \quad i, j, t \quad (3.8)$$

As long as there are diminishing returns to resource j , the shadow price is a decreasing function of the quantity of resources committed to fire i . The remaining variables shift the marginal benefit of fire manager i up or down. The shadow price, λ_{ijt} represents the social marginal cost of allocating resource j to fire manager i in terms of damage on all fires $-i$. The solution to the regional command unit's optimization problem implies that λ_{ijt} is a function of the exogenous characteristics that influence all fires $-i$ at time t .

$$\mu_{ijt} = \mu(\bar{y}_{ijt}; \bar{y}_{-ijt}, w_{-ijt}, \mathbf{v}_{-it}(a_{-it}), \mathbf{x}_{-it}, I) \quad \forall \quad i, j, t \quad (3.9)$$

The marginal social cost of allocating resource j to fire i at time t is an increasing function of $\bar{y}_{ijt}$. The remaining variables shift the marginal benefit of fire managers $-i$; and are therefore, expected to shift the social cost.

By the equilibrium condition in equation (3.7), $\lambda_{ijt} = \lambda_{-ijt} = \mu_{jt}$ for each fire i , resource j , and time t . Therefore, equations (3.8) and (3.9) form a system of structural equations. However, I as a researcher, do not observe λ , but I do observe the quantity, $\bar{y}_{ijt}$, of resource j allocated to fire i . The equilibrium condition in equation (3.7) implies the existence of the reduced-form equation

$$\bar{y}_{ijt} = y(\overbrace{w_{ijt}, \mathbf{v}_{it}(a_{it}(f_{it})), \mathbf{x}_{it}}^{\text{Demand Factors}}, \overbrace{\bar{y}_{-ijt}, w_{-ijt}, \mathbf{v}_{-it}(a_{-it}(f_{-it})), \mathbf{x}_{-it}, I}^{\text{Supply Factors}}) + \varepsilon_t \quad (3.10)$$

In the theoretical model, ε_t , represents the uncertainty about the growth of the fire's energy stock. In the empirical model, the error term ε_t captures the uncertainty about weather, fire behavior, and the ignition of new fires. The number of assets at risk depends on the growth of the fire, which implies that many of the factors that influence the allocation of response resources are uncertain outcomes. Intuitively, both fire managers and regional command units request and commit resources prior to learning the outcome of the random

variable. Therefore, these so called supply and demand factors are expectations formed in period $t - 1$ that influence the committed resources observed in period t .

3.2.3 Hypotheses

Weather factors such as temperature, windspeed, and humidity impact the physical process of wildfire, which cumulatively impact wildfire outcomes. Since response resources are committed prior to the realization of weather outcomes, allocation decisions are based on forecasted weather. Studies of the physical process of wildfire find that windspeed and temperature facilitate fire spread while humidity inhibits fire spread (Finney, 1998). Therefore, I assume that growth of the fire's energy stock is increasing in windspeed and temperature, and decreasing in humidity. An expected increase in fire growth increases the potential losses, and thus, the marginal value of resource j .¹⁵ The following three hypotheses pertain to the impact of forecasted weather on response resource allocation:¹⁶

Hypothesis 1. *An increase in the forecasted temperature increases the number resources committed to fire i .*

Hypothesis 2. *An increase in the forecasted windspeed increases the number resources committed to fire i .*

Hypothesis 3. *An increase in the forecasted relative humidity decreases the number resources committed to fire i .*

The impact of weather on wildfire cost, size, and structure damage is conditional on hypotheses 1, 2, and 3. If fire managers correctly forecast the weather and receive their

¹⁵Finney, Grenfell, and McHugh (2009) argue that fire managers exploit opportunities during periods of low fire spread.

¹⁶To the extent that weather is homogenous within a region, a change in weather may affect all fires within the region similarly and show no significant impact on the quantity of resources allocated to fire i . The reader may think of an ambiguous change in the equilibrium quantity of a good when the same exogenous factor shifts demand outward and supply inward. I include data on forecasted weather on all fires $-i$ to account for this possibility.

requested resources in anticipation of wildfire behavior, the impact of high wind and temperature on wildfire cost, size, and structure damage may be ameliorated, or even reversed. If on the other hand, weather is incorrectly forecasted or fire managers do not receive their requested resources, high wind and temperature would increase fire growth and lead to larger and more expensive wildfires that cause more damage.

When the fire manager faces a resource constraint, an increase in the number of threatened assets translates into a larger marginal benefit, λ_{it} , for resources used in protection effort.

Hypothesis 4. *An increase in the number of threatened assets on fire i increases the allocation of protection resources j to fire i . Similarly, an increase in the number of threatened assets on fire $-i$ decreases the allocation of protection resources j to fire i .*

The model in chapter 2 abstracts from the allocation of response resources by considering the individual fire manager and regional command unit as a single agent. While the results of the trivariate hazard model suggest that threatened assets increase wildfire cost and size, the reduced-form model is unable to distinguish between direct and indirect effects that flow through resource allocation decisions. In contrast, this analysis distinguishes between these effects by estimating a first-stage model of response resource allocation. Therefore, threatened structures should only affect wildfire cost, and size and structure damage through an increase in protection resources.

Hypothesis 5. *An increase in the number of threatened residential structures indirectly affects wildfire cost, size, and structure damage through a reallocation of response resources.*

The regional command unit faces an exogenous resource constraint at any point in time. If there exists enough demand for response resources, the constraint will bind and μ is a decreasing function of the maximum available resources. Therefore, each fire i is more

likely to receive their requested quantity of resources when the maximum available resources increase.

Hypothesis 6. *An increase in the total available resources in the region increases the allocation of resources to fire i .*

3.3 Data and Empirical Methods

The dataset used in this study is compiled from several publicly available datasets. Table 12 contains the data sources and a brief description of the data gathered from each source.

The Incident Status Summary (ICS-209) data are based on reports completed by wildfire managers intermittently throughout the wildfire response effort. These data include the response resources committed to the fire at various stages during the fire, weather, geographic characteristics, and relevant wildfire outcomes such as cost, size, and damage to structures on large wildfires in the U.S. from 2001 to 2010.¹⁷ ICS-209 reports are filed for fires that exceed 300 acres in grass and brush, or 100 acres in timber, or receive type 1 and 2 crew teams (NICC, 2012), which creates truncation that may bias the regression estimates of fire size downward (Yoder and Gebert, 2012).

The ICS-209 data contain the number of response resources committed to fire i by agency. The resources are aggregated by agency because regional command units coordinate the distribution of units amongst various agencies. The resources are then grouped by the tasks a resource is designed to accomplish (e.g., Type 1, 2, and 3 helicopters are aggregated to form the variable Helicopter). However, type 1 and 2 firefighting crews are not aggregated because of the significant differential in training, autonomy, and expected productivity.¹⁸

¹⁷These data have been criticized for inaccuracies and inconsistent reporting of daily response costs (Gude et al., 2013; Gebert, Calkin, and Yoder, 2007). However, the data contain microlevel information on the daily management of a significant proportion of large fires across the U.S., and there is no reason to believe that missing data or input errors occur systematically in the data. Therefore, the consequence on inference should be one of efficiency rather than bias.

¹⁸Type 1 crews are usually full time employees with high-level training, whereas type 2 crews are often

The ICS-209 data distinguish between single resources and strike teams. A strike team is a defined set of resources with a common leader (FIREScope, 2012), which implies that one strike team consists of more than one single resource. Based on the minimum strike team requirements as defined in FIREScope (2012), I multiply the number of strike teams by the number of resource type j and sum the result with the single resource observations.¹⁹

The ICS-209 data also includes variables on the wildfire outcomes and conditions throughout the fire. Wildfire cost and size are reported as cumulative outcomes and the number of structures threatened, damaged, and destroyed are reported in each period. The variable Thr. Residential almost perfectly represents the notion of potential damage to structures developed in the theory. However, fire managers engaged in suppression also care about containment of the fire perimeter. While there are no variables that explicitly provide this information, a combination of fire size and percent containment are used to generate an instrument for the uncontrolled perimeter. By treating the fire size as the area of a circle, one can use the radius to calculate the perimeter at any observation. This lower bound approximation of a perimeter is then multiplied by the (1-% contained) to generate the covariate uncontrolled perimeter.²⁰

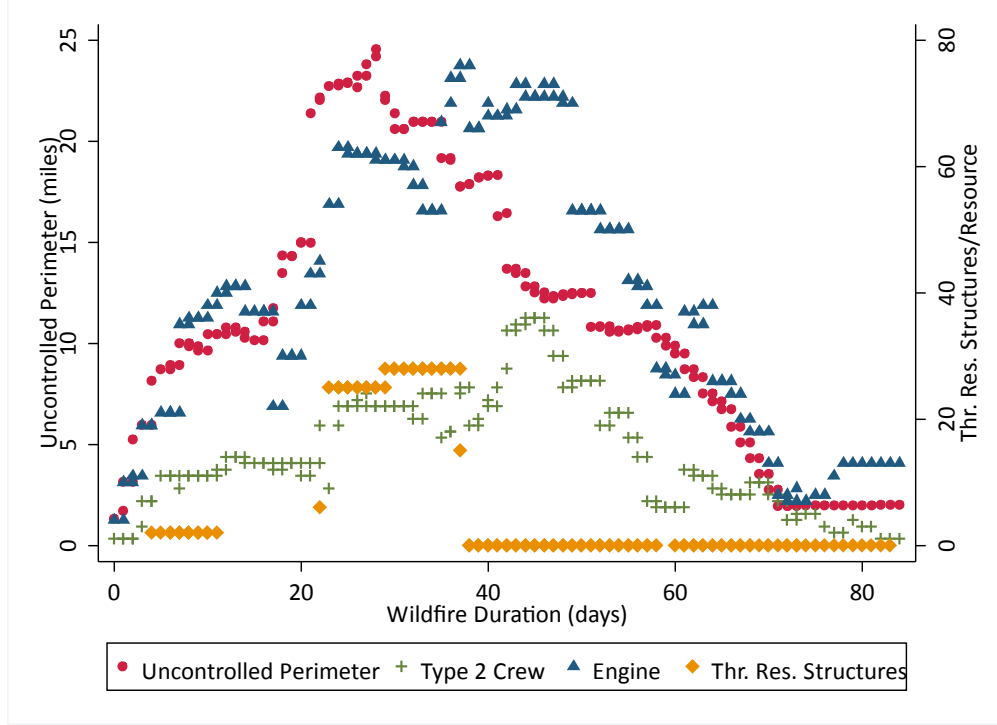
Figure 6 contains a plot of the covariates Uncontrolled Perimeter, Threatened Residential over the course of the Siskiyou Complex wildfire that occurred in Northern California. Type 2 Crew is chosen as a representative resource although, other resources follow a similar pattern. The figure illustrates the response of resource allocation to a growing Uncontrolled Perimeter and an increase in Thr. Residential. As the Uncontrolled Perimeter continues to grow (until day 28) the number of Type 2 Crew members increases but at a slower rate. In

comprised of seasonal firefighters with limited training.

¹⁹When resource j data is missing at time t within a fire for which other resource $-j$ data is non-missing, the missing observations are assumed to denote a lack of change in the number of resources committed to fire i and are filled by resource data at $t - 1$. If there is no prior non-missing data, the observation is replaced with a zero. Without replacement of intermittently missing data, the entire observation would be excluded from the estimation, which would confound the use of lagged covariates.

²⁰The formula for this calculation is $\text{Uncontrolled Perimeter} = 2\pi\sqrt{(\text{Area}/\pi)}(1 - \% \text{contained})$.

Figure 6: Plot of Uncontrolled Perimeter, Thr. Residential, and Type 2 Crew over duration of Siskiyou Complex.



addition, the number of Type 2 Crew members increases in response to a sharp increase in the number of Thr. Residential. This figure clearly illustrates the dynamic nature of wildfire management in the data.

The response resource allocation equations derived in section 3.2 indicate that the resources committed to fire i depend on the same conditions that affect all fires $-i$ within the region. Therefore, I develop an algorithm to search the dataset for wildfires burning in the region within the past 48 hours and collect data on the total number of response resource _{j} committed, average forecasted weather, total number of threatened residential structures, total number of potential evacuations, and total length of uncontrolled perimeter. These are imperfect measures of the factors that influence the allocation of resources within a region because the truncated ICS-209 dataset does not contain every fire. However, they should be highly correlated and provide good instruments for the true but unknown values. Details of the algorithm can be found in B.3.

The National Interagency Fire Management Integrated Database (NIFMID) contain many additional factors that influence wildfire and fire management behavior. These data are cross sectional and represent a summary of the entire suppression effort, particularly whether a fire was managed by federal, state, or private agencies as well as the slope, elevation, aspect, and fuel model at the point of ignition. In addition, the NIFMID dataset contains variables redundant to the ICS-209 data such as start date, final cost, final size, location (latitude and longitude), and fire name.

Both ICS-209 and NIFMID datasets contain information relevant to this analysis, however neither contain a common identifier that would facilitate a simple merging of the two datasets. Therefore, I develop an algorithm to merge the datasets based on an index comprised of word matches based on name, location, cost, size, and start date. A detailed description of the algorithm can be found in appendix B.2.

3.3.1 Econometric Model

The econometric model of wildfire cost, size, and damage consists of two stages. In the first stage, I estimate the response resource allocation equations with a dynamic panel model and generate predicted values for the number of response resources committed to fire i at time t . These predicted values instrument the endogenous response resource covariates in the second-stage hazard equations of wildfire cost and size, and zero-inflated negative binomial equation of wildfire damage to structures. Since the regressions in the first-stage resource allocation equations provide information about a subset of hypotheses developed in section 3.2, I devote attention to the estimation method and results separate from the second stage estimation.

First-Stage Model: Response Resource Allocation Equations

I estimate the response resource allocation equations (3.10) with the dynamic panel estimator commonly referred to as the Arellano-Bond systems estimator (Arellano and Bover, 1995; Blundell and Bond, 1998). Response resource allocation is based on the evolution of the wildfire over time, which implies that resource allocation is a dynamic process. Frictions also exist in the transportation of response resources, which contribute to the dynamic nature of the problem.²¹ In addition, many factors that influence the allocation of response resources are themselves influenced by the use of response resources over the course of the wildfire, which implies that many regressors are likely endogenous. The Arellano-Bond systems estimator exploits the panel structure of the data to create instruments for the lagged dependent variable and endogenous regressors.

The Arellano-Bond systems estimator jointly estimates a system of two equations: one in levels, and one in first differences.²²²³

$$\bar{y}_{ijt} = \alpha_j \bar{y}_{ij,t-1} + \mathbf{x}_{i,t-1} \boldsymbol{\beta}_j + \mathbf{c}_{ijt} \boldsymbol{\gamma}_j + \varepsilon_{ijt} \quad \text{where } \varepsilon_{ijt} = u_{ij} + v_{ijt} \quad (3.11)$$

$$\Delta \bar{y}_{ijt} = \alpha_j \Delta \bar{y}_{ij,t-1} + \Delta \mathbf{x}_{i,t-1} \boldsymbol{\beta}_j + \Delta \mathbf{c}_{ijt} \boldsymbol{\gamma}_j + \Delta v_{ijt} \quad (3.12)$$

where $\bar{y}_{ijt}$ is the number of resources of type $j = \{\text{firefighting crews, helicopters, fixed-wing aircraft, tractors, and engines}\}$ committed to fire i at time t , $\mathbf{x}_{i,t-1}$ is a lagged vector of covariates, $\mathbf{c}_{ijt}$ is a vector of contemporaneous control covariates, α_j , $\boldsymbol{\beta}_j$, and $\boldsymbol{\gamma}_j$ are coefficients for resource j , and Δ is a first-difference operator. Covariates in both $\mathbf{x}$ and $\mathbf{c}$ may

²¹Arellano and Bond (1991) study firm-level employment, which they argue is dynamic because it is costly to hire and fire workers. In fact, the allocation of resources within a firm provides a direct analogy to the resource transfer frictions faced by regional command units and individual fire managers.

²²The original Arellano-Bond model estimates only the first difference equation. The systems estimator generates additional moment conditions, and also allows the inclusion of covariates fixed throughout the panel, which are differenced out in the first difference equation. As with any random effects estimator, any fixed covariate are assumed to be uncorrelated with the fixed component of the error term.

²³I implement the Arellano-Bond systems estimator with *xtabond2* for the Stata statistical software package (Roodman, 2006).

be endogenous and are instrumented by a vector of covariates $\mathbf{z}$ that may include l lags of the y and covariates in $\mathbf{x}$ and $\mathbf{c}$.

Each resource allocation equation includes lagged covariates representing weather and threatened assets on both fire i and fires $-i$. Additional covariates are included to control for the evolution of the wildfire. The lagged values are chosen over their contemporaneous counterparts because the observed committed resources at time t are based on decisions made with all available information at time $t - 1$. This justification for the lagged structure of covariates is also consistent with the assumption in the theoretical model that total number of resources available to fire manager i are fixed at any point in time.

I include the lagged values of Forecasted Temperature, Forecasted Windspeed, and Forecasted Humidity on fires i and $-i$ to test the hypothesis that forecasted variation in the weather impact the request and receipt of response resources. Lagged Thr. Residential and Potential Evacuation on fires i and $-i$ are included to quantify the variable impact of potential damage to a highly-valued asset on each type of response resource. Lagged Uncontrolled Perimeter is included to control for the progression of the response effort and isolate the impact of the weather and threatened assets covariates. I also include Day of Year to account for the seasonality of wildfire response.

When multiple fires are simultaneously in need of response effort, the regional command unit's resource constraint is likely to bind. Therefore, I include the variable Response Resources $_j -i$, which is the sum of resource j committed to all fires within the region, to account for changes in total resource availability within a region.²⁴

The Arellano-Bond estimator exploits the dynamic nature of panel data by using lagged covariate values, as well as external covariates, as instruments for the lagged dependent variable and any endogenous covariates. Use of lags as instruments is justified when the

²⁴The inclusion of covariates with information on other fires within the region also promotes the independence of observations between fires (panels), which is an assumption of the Arellano-Bond systems estimator.

observation-specific error term v_{ijt} is not serially correlated (Roodman, 2006). Arellano and Bond (1991) construct a test of autocorrelation in l lags of first-difference residuals to validate the inclusion of $l + 1$ and beyond lags of the dependent variable and any endogenous covariates. I use this test to determine the optimal lag structure of the instrument matrix for each equation discussed below.²⁵

In addition to the lagged values of y and $\mathbf{x}$, I include external instruments that indirectly influence resource allocation decisions through already included covariates. A binary variable indicating a subjective potential for evacuation and a count variable representing the number of injuries also provide information about resource allocation over the course of the wildfire. Because these variables are also endogenous, they are lagged at the same distance as the endogenous covariates in $\mathbf{x}$.

Estimation of the Arellano-Bond systems estimator is based on a set of theoretical moment conditions $E[\mathbf{z}\mathbf{e}] = 0$ where $\mathbf{z}$ is a matrix of valid instruments and $\mathbf{e} = \mathbf{y} - \mathbf{x}\boldsymbol{\beta}$. When the system is overidentified, not all moment conditions may be satisfied and the problem amounts to choosing a weighting matrix to obtain the most precise estimates. I use the two-step version of the estimator, which is robust to within-panel heteroskedasticity and autocorrelation (Roodman, 2006).²⁶ Standard errors of model parameters are estimated based on the two-step estimator correction proposed by Windmeijer (2005).

²⁵The instrument matrix is constructed such that $E[\mathbf{z}'\hat{\mathbf{e}}] = 0$ which implies a set of moment conditions $\sum_i y_{ij,t-2}\hat{e}_{ijt} = 0$ for each j , and $t > 2$. By construction, the number of moment condition is quartic in T , which can be almost 50 on large fires in the dataset. A theoretically consistent way to reduce the number of moment conditions without dropping these large fires from the dataset is to “collapse” the instrument matrix such that moment condition becomes $\sum_{i,t} y_{ij,t-2}\hat{e}_{ijt} = 0$ for each j since the sum of zeros is zero. This method reduces the likelihood of overidentification (Roodman, 2006).

²⁶Any symmetric positive semidefinite weighting matrix $\mathbf{A}$ yields consistent parameter estimates, which implies that one can estimate a preliminary regression (first step) to obtain estimated errors. The covariance matrix of the preliminary estimation is inverted to provide a robust second-step weighting matrix $\mathbf{A}_r = (\mathbf{z}'\boldsymbol{\Omega}\mathbf{z})^{-1}$.

Second Stage Model: Wildfire Cost, Size and Damage

The second-stage regression models quantify the impact of response resources, environmental characteristics, and economic factors on final wildfire cost, size, and damage to residential structures. I estimate the cost and size equations with a hazard model as in chapter 2. In theory, one could also treat damage to residential structures as a cumulative outcome like cost and size. However, hazard models attribute covariate values to intervals in the progression of the fire, and data limitations would yield very few observations that fit this criteria. Therefore, I estimate the damage equation with a zero-inflated negative binomial regression.

I use a Cox shared frailty (hazard) model to estimate final wildfire cost and size (Cox, 1972). The term shared implies that all observations within a fire share a common frailty which captures the correlation between within-panel observations. The wildfire cost and size models are estimated by maximum partial likelihood the methods of which are detailed in Kalbfleisch and Prentice (1980).

The residential structure damage model is estimated by a zero-inflated negative binomial (ZINB) model that accounts for the count nature of the data and the abundance of zeros observed in the data. The negative binomial model accommodates over dispersion by mixing the Poisson and Gamma distributions; although, other justifications of the model exist (Cameron and Trivedi, 2005). The model is given by²⁷

$$damage_i \sim \text{Poisson}(\mu_i) \quad \text{where} \quad \mu_i = \exp\{x_i\beta + \nu_i + \varepsilon_i\} \quad \text{and} \quad e^{\nu_i} \sim \Gamma\left(\frac{1}{\alpha}, \alpha\right).$$

This mixing Gamma distribution is parameterized $\Gamma(a, b)$ such that the mean is $ab = 1$ and the variance is $ab^2 = \alpha$ which accounts for the over dispersion.

²⁷The notation used to describe the negative binomial model is chosen to remain consistent with the literature and does not necessarily correspond to the notation used to describe the Arellano-Bond systems estimator.

Despite the media attention that damaged and destroyed residential structures receive, they occur less frequently than the Poisson and negative binomial would predict because not all wildfires threaten residential structures. The over abundance of zeros in the data create bias if left unaddressed. The zero-inflated model treats the problem as one of sample selection in which a latent variable describes the process by which the dependent variable $damage = 0$ or $damage > 0$. The ZINB model is defined by Cameron and Trivedi (2005) as

$$g(damage) = \begin{cases} f_1(0) + (1 - f_1(0))f_2(0) & \text{if } damage = 0 \\ (1 - f_1(0))f_2(damage) & \text{if } damage > 0 \end{cases} \quad (3.13)$$

where $f_1(\cdot)$ is a logit model and $f_2(\cdot)$ is a negative binomial density. The logit portion of the likelihood function estimates the latent variable that determines whether structures are at risk of damage. Fortunately, I have data on the number of threatened residential structures that provides direct information about this latent variable. In addition to lagged Thr. Residential, I include Human Caused, WUI Interface, WUI Intermix, and County Road Miles as covariates that increase the probability that a home is at risk.

The second stage shared frailty and ZINB models accommodate time-varying as well as time-invariant covariates. The ICS-209 data used to estimate the first-stage model is merged with the NIFMID data using the algorithm described in appendix B.2. This merged dataset contains time-invariant covariates that account for environmental and economic characteristics of a wildfire. I instrument the response resource covariates in the second-stage models with predicted values from the first-stage Arellano-Bond equations. Because of the prevalence of missing data in the ICS-209 dataset and the lack of a unique identifier between the ICS-209 and NIFMID datasets, a substantial amount of data is lost between the first and second stage estimations. I have no reason to believe that the data are missing systematically. Therefore, the consequence should be one of efficiency and not bias. The summary

statistics of the data subsets used in each regression are contained in tables 14, 15, and 16 in appendix B.4.

The ZINB model is not inherently dynamic, which is incongruous with the theory and other empirical models. Damage to structures early in the response process may be fundamentally different than damage in later stages of a fire. In an effort to capture the dynamic features of the problem with a static model, I calculate a cumulative sum of the predicted response resources committed over the course of the fire and divide it by the duration of the fire in days. This transformation is applied to all resource types and is used in the ZINB model of structure damage.

Current Windspeed, Temperature, and Humidity are used in the second-stage models to control for the physical characteristics that impact fire growth. In contrast to the first-stage regressions in which forecasted weather was used, current weather captures the direct impact of covariates on wildfire outcomes when endogenous response resources are instrumented.

In addition to ICS-209 data on threatened residential properties, I use county level log median home value from the 2010 U.S. Census (Census, 2012), and the acres in a county classified as either wildland-urban interface or wildland-urban intermixed. The interface classification is assigned to land with six or more homes per square kilometer with less than 50% vegetation located within 2.414 kilometers of land covered by over 75% vegetation. The intermixed classification contains land covered by more than 50% vegetation and contains six or more homes per square kilometer. These two landscape types pose very different challenges to fire managers and I expect the parameter estimates on the covariates to differ. Based on the model of wildfire response in section 3.2, intermixed landscape receives more protection effort, which increases cost and allows the fire to grow larger, but should save structures from damage. In contrast, interface landscape receives more suppression effort, which reduces cost by exploiting economies of scale in fire line construction, decreases fire size, and may or may not reduce the damage to residential structures.

Other NIFMID variables are included as controls for the environment. Day of Year is converted into radians and transformed by $\cos(x)$. Conditions conducive to fire growth are likely to occur in the summer months, which occur in the $[-1, 0]$ range of a cosine function. Elevation and slope account for the accessibility of the terrain during the initial attack. Timber takes a 1 if the reported fuel model is H, R, E, P, U, or G, and a 0 otherwise. Private and State Management capture the differences in stated priorities across agencies (Federal is the omitted dummy variable). Human Caused is a binary covariate (Lightning-caused is omitted) that captures differences in discovery and response time. Lightning-caused fires often occur further from development and grow larger before discovery and response.

3.4 Results

This section provides a discussion of the first- and second-stage estimation results.

3.4.1 First-Stage: Resource Allocation Equations

Table 2 contains the coefficient estimates and associated p-values of covariates in the resource allocation equations where the dependent variable is the number of response resources allocated to fire i . The bottom of the table includes the number of observations, individual fires, and the number of instruments used in each model. I also report the results of a model χ^2 test and the Hansen test of overidentification. The null hypothesis of the Hansen test is that the system of moment conditions is not overidentified.²⁸

Resource Allocation Dynamics

The lagged dependent variable in each response resource equation provides information on the mobility of a resource and accounts for the dynamics of wildfire activity (modeled in

²⁸The Sargan test of overidentification is not appropriate for the two-step version of the Arellano-Bond systems estimator.

Table 2: Parameter estimates from Arellano-Bond systems estimation of response resource allocation equations.

	Type 1 Crew		Type 2 Crew		Helicopter		Dozer		Engine	
	β	P-val	β	P-val	β	P-val	β	P-val	β	P-val
Resource	0.967	(0.000)	0.549	(0.000)	0.691	(0.000)	0.766	(0.000)	0.905	(0.000)
Resource $-i$	0.017	(0.262)	0.008	(0.072)	-0.002	(0.609)	0.004	(0.604)	0.000	(0.969)
Forecasted Temperature	0.002	(0.975)	-0.036	(0.044)	-0.004	(0.524)	-0.001	(0.953)	-0.005	(0.839)
Forecasted Temperature $-i$	0.062	(0.475)	0.041	(0.054)	0.007	(0.433)	0.027	(0.075)	0.051	(0.042)
Forecasted Windspeed	0.139	(0.102)	-0.030	(0.519)	0.008	(0.545)	0.002	(0.930)	-0.074	(0.323)
Forecasted Windspeed $-i$	-0.084	(0.310)	0.009	(0.843)	-0.006	(0.608)	0.010	(0.676)	0.153	(0.051)
Forecasted Humidity	-0.061	(0.273)	-0.038	(0.151)	-0.014	(0.149)	-0.024	(0.119)	-0.033	(0.220)
Forecasted Humidity $-i$	0.054	(0.429)	0.037	(0.197)	0.009	(0.359)	0.025	(0.117)	0.019	(0.462)
Thr. Residential	1.221	(0.062)	0.229	(0.123)	0.038	(0.420)	0.072	(0.464)	-0.019	(0.916)
Thr. Residential $-i$	-0.220	(0.881)	4.452	(0.394)	-0.013	(0.924)	0.794	(0.433)	-8.134	(0.510)
Potential Evacuation	1.870	(0.088)	0.969	(0.111)	0.617	(0.000)	0.836	(0.164)	-0.245	(0.822)
Potential Evacuation $-i$	-0.074	(0.605)	-0.108	(0.447)	-0.042	(0.117)	-0.011	(0.943)	0.191	(0.051)
Uncontrolled Perimeter	0.099	(0.091)	0.065	(0.055)	0.049	(0.001)	0.133	(0.090)	0.115	(0.070)
Uncontrolled Perimeter $-i$	-0.006	(0.395)	-0.002	(0.503)	-0.001	(0.487)	-0.004	(0.104)	-0.004	(0.583)
Day of Year	1.297	(0.426)	-2.825	(0.002)	0.067	(0.767)	0.217	(0.812)	-0.430	(0.614)
Constant	-6.709	(0.087)	0.567	(0.679)	0.760	(0.078)	-2.600	(0.048)	-3.144	(0.054)
Observations	6826		6826		6826		6826		6826	
Fires	642		642		642		642		642	
Instrument Count	128		98		96		32		56	
χ^2 p-val	0.0000		0.0000		0.0000		0.0000		0.0000	
Hansen p-val	0.5160		0.2665		0.5304		0.7016		0.5152	

All covariates are lagged ($t - 1$) except for Day of Year

the theory as the wildfire stock). The estimates in each model are highly significant. The magnitudes of the lagged dependent variable in the Type 1 Crew and Engine models (0.967 and 0.905) imply that the allocation of both resources is highly dependent on the allocation in $t - 1$. One possible explanation is that Type 1 Crews and Engines are often permanently employed by a local dedicated wildfire unit, and are generally assigned to wildfires in their locale. In contrast, the coefficient estimates on Helicopters, Type 2 Crews, and Dozers suggest that these resources may be moved between fires more frequently.²⁹

Recall that the covariate Resource $-i$ is an instrument for the total number of resource j available to the regional command unit for dispatch. When the regional command unit has more resources available, all fires within the region should receive a greater allocation. Hypothesis 6 predicts that this coefficient estimate should be positive in each model. This is the case for Type 1 Crew, Type 2 Crew, and Dozer (0.017, 0.010, and 0.003), although, the Type 2 Crew model is only statistically significant at the 10% level.

Forecasted Weather

Forecasted weather covariates are chosen over their observed counterparts to isolate the impact on decision-makers rather than fire behavior. The statistical significance on many of the parameters is low which may indicate that forecasted increases in measured weather simply increases the uncertainty about fire behavior.³⁰ In response, both fire managers and regional command units focus on strategic goals and place less emphasis on weather outcomes.

²⁹Roodman (2006) suggests an ad hoc specification test based on the pooled OLS and fixed-effect estimators. The existence of dynamic panel bias, caused by a lagged dependent variable, implies that the pooled and fixed-effects parameter estimate of the lagged dependent variable are biased but provide a theoretical upper and lower bounds for the Arellano-Bond estimate. Appendix 19 contains a table with the lagged dependent variable estimates from the Arellano-Bond, pooled OLS, and fixed effect models for comparison.

³⁰Wald tests of joint significance are also conducted on the pair of weather coefficients corresponding to fires i and $-i$ for each resource j . The results fail to reject the null that both coefficient estimates are jointly equal to zero in all resource models except for Engine, where Temperature and Windspeed reject H_0 at 5% significance.

The coefficient estimates on Forecasted Temperature are negative in all model except Type 1 Crew, which contradicts hypothesis 1. The estimates on average forecasted temperature on all other fires within the region are positive for all resources and reinforce the estimates of forecasted temperature on fire i . The windspeed estimates tell a similar story with negative coefficients in the Type 2 Crew, Dozer, and Engine models. The windspeed coefficient is positive, and supports hypothesis 2, in the Type 1 Crew and Helicopter models (while only significant in the Type 1 Crew model). These results may imply that fire managers perceive temperature increases as potentially dangerous to all resources, but trust that highly trained resources (type 1 crews and helicopters) can avoid hazardous situations.

The forecasted humidity coefficient estimates are negative and support hypothesis 3. The estimates of forecasted humidity on other fires in the region imply that a decrease in expected fire growth makes those resources available for fire i .

Threatened Residential Structures

Thr. Residential and Potential Evacuation are included in the model to capture the incentives of both individual fire managers and regional command units to protect threatened assets. The difference between the covariates is based on the degree to which residential structures are threatened. A potential for evacuation conveys a more serious threat to the regional command unit.

The coefficient estimates on Thr. Residential and Potential Evacuation are positive in almost all models (except Engine, but the estimates are not significant), which provide support for hypothesis 4. The magnitude of the coefficient on Thr. Residential may contain information about the fire manager's perception of the resource's ability to mitigate damage. The estimate in the Type 1 Crew model (0.012) implies that an additional type 1 crew member is allocated to fire i when the number of threatened residential structures increases by 100 (alternatively, a 20-man crew is allocated to fire i when 1,600 structures are threatened).

Controls

The covariates Uncontrolled Perimeter and Day of Year are included in each model to account for other factors that influence response resource allocation. By controlling for the evolution of the wildfire, I hope to better isolate the effect of weather and threatened assets on response effort.

Uncontrolled Perimeter is an approximation for the amount of effort still required to contain fire i . Since the covariate is calculated based on fire size (in square miles) and percent of containment, the variable is endogenous and is instrumented along with the other endogenous covariates. This covariate captures the progression of the response effort and explains much of the variation that would otherwise be captured by the lagged dependent variable. The coefficient estimates are positive and significant in all models indicating that more response resources are allocated to fire i when either the percentage contained is low or the burned area is large. The coefficients on Uncontrolled Perimeter $-i$ are all negative as expected. The covariate is calculated in miles so an additional 10 miles of uncontrolled perimeter earns 1.3 dozers.

The cosine transform of Day of Year implies that a negative coefficient indicates more resources are allocated in the summer months (when the $\cos(x) < 0$) and less in the winter months (when the $\cos(x) > 0$). The coefficient in the Type 2 Crew model is negative which is expected given that Type 2 Crews tend to consist of seasonal staff.

Long-Run Marginal Effects

In addition to the short run marginal effects presented in table 2, I present long-run marginal effects in appendix ?? table 17. The long-run marginal effects provide information about

the impact of a unit change in a covariate over the entire suppression effort.³¹ The long-run marginal estimates of Thr. Residential in the Type 1 Crew equations is not significant at a 10% level, despite its short-run significance. However, weather factors such as Forecasted Temperature on fire i and on fires $-i$ do remain significant in the long-run. These results may indicate that while fire managers quickly react to short-run changes of threatened assets, weather forecasts impact long-run strategies. These results do not imply that short-run changes in resource allocation have no impact on wildfire outcomes. In fact, the theoretical results imply that even short-run reallocation of resources from suppression to protection allow the fire to grow and ultimately cost more to suppress. The next section investigates the impact of resource commitment, and the direct impacts of weather and threatened residential structures on wildfire cost, size, and structure damage.

3.4.2 Second-Stage: Wildfire Cost, Size, and Structure Damage

Table 3 contains the parameter estimates of the hazard regressions of wildfire cost and size, as well as the ZINB regression of residential structure damage. The bottom half of the table contains the parameter estimates from the Logit Zero-Inflation Equation and the model summary statistics.³² The existence of unobserved heterogeneity in the hazard regression

³¹Long-run marginal effects, reported in table 17, are derived under the assumption that the system is in equilibrium, which implies,

$$\begin{aligned}\bar{y} &= \alpha \bar{y} + \mathbf{x}\boldsymbol{\beta} + \mathbf{c}\boldsymbol{\gamma} \\ \bar{y} &= \frac{1}{(1 - \alpha)} (\mathbf{x}\boldsymbol{\beta} + \mathbf{c}\boldsymbol{\gamma}).\end{aligned}$$

The marginal effect of x_1 , i.e., Thr. Residential, is

$$\frac{\partial \bar{y}}{\partial x_1} = \frac{\beta_1}{(1 - \alpha)}.$$

³²The variation in the number of observations and fires included in each regression equation is due to the structure of hazard models and missing observations. The shared frailty hazard model estimates the impact of a set of covariates on the probability that the fire is extinguished in the next interval of growth in cost or size. The covariate information is incorporated into the model by associating a covariate state with an interval of growth in cost or size. If there is no growth in fire size or cost, the model interprets no change in the dependent variable regardless of changes in the covariates. Therefore, observations for which fire cost or

models is tested with a likelihood ratio test distributed χ^2 . The tests suggest that there does exist unobserved fire-level heterogeneity in costs (P-value=0.000), but not in fire size (P-value=0.493).³³ The Vuong test finds evidence (P-value=0.011) that there exists two separate data-generating processes leading to zeros in the structures variable.

The instrumented response resource covariates account for the indirect impacts of weather and threatened assets on wildfire cost, size, and structure damage. The set of regressions in this section are interpretable as direct impacts. Regression estimates of a shared frailty model is complicated by the conditionality of the estimates on the unobserved heterogeneity parameter. Therefore, I focus on the sign of the parameter estimates and the magnitude relative to other covariates.

The interpretation of parameter estimates of a proportional hazard model differ from that of a conventional linear model. The coefficients shift the baseline hazard function, which represents the probability that an event occurs in the next interval of progress conditional on having persisted until now. Therefore, a positive coefficient increases the hazard rate, which decreases the magnitude of the expected outcome (wildfire cost and size).

The Logit Zero-Inflation equation estimates the impact of a set of covariates on the probability that an observation is certainly zero, rather than described by the negative binomial distribution. Lagged Thr. Residential is a natural indicator of whether a structure will be damaged or destroyed. Human-caused fires often occur near residential structures, which implies Human Caused is a good instrument for proximity of fire ignition to residential structures. County Road Miles captures the extent to which a county's land is developed and thus, susceptible to wildfire. The WUI covariates are included to capture county-level

size do not grow provide no additional information and are dropped from the regression. In order to maintain as many observations as possible, I estimate each model separately and always keep the latest observation if observations are dropped.

³³This finding is consistent with the estimates of unobserved heterogeneity in the fire size component of the trivariate shared frailty hazard model estimated in chapter 2. The results of the trivariate hazard model also indicate that correlation between the fire cost and size components is not statistically significant.

Table 3: Parameter estimates of hazard and ZINB models of wildfire cost, size, and damage.

	Wildfire Cost		Wildfire Size		Structure Damage	
	β	P-val	β	P-val	β	P-val
Type 1 Crew*	0.003	(0.044)	0.001	(0.339)	-0.001	(0.821)
Type 2 Crew*	-0.031	(0.151)	-0.013	(0.320)	-0.126	(0.059)
Helicopter*	-0.275	(0.000)	0.024	(0.482)	0.356	(0.017)
Dozer*	-0.069	(0.023)	-0.112	(0.000)	-0.184	(0.159)
Engine*	-0.024	(0.000)	0.010	(0.041)	-0.000	(0.991)
Thr. Residential _{t-1}	-0.004	(0.705)	0.003	(0.621)	-0.013	(0.658)
Log(Med Home Value)	-0.990	(0.000)	-0.301	(0.067)	-3.371	(0.023)
WUI Intermix $\times$ Res _{t-1}	-0.000	(0.536)	-0.000	(0.014)	0.000	(0.853)
WUI Interface $\times$ Res _{t-1}	0.000	(0.340)	0.000	(0.060)	-0.000	(0.843)
Log(Med Home Value) $\times$ Res _{t-1}	0.000	(0.748)	-0.000	(0.653)	0.001	(0.616)
Windspeed	-0.016	(0.298)	-0.016	(0.188)	0.087	(0.060)
Temperature	0.013	(0.196)	0.017	(0.048)	0.017	(0.617)
Humidity	0.015	(0.033)	0.032	(0.000)	-0.019	(0.316)
Day of Year ^a	0.339	(0.401)	0.364	(0.151)		
Elevation (1000ft)	0.161	(0.003)	0.058	(0.153)		
Slope	-0.010	(0.031)	-0.002	(0.425)		
Timber	-0.997	(0.000)	0.073	(0.654)	-2.379	(0.223)
Private Management	0.378	(0.709)	1.460	(0.046)		
State Management	-0.452	(0.221)	0.242	(0.306)	-2.797	(0.020)
Constant					39.876	(0.037)
Heterogeneity Parameter ^b	0.882	(0.000)	0.000	(0.493)	1.043	(0.000)
Logit Zero-Inflation Equation						
Thr. Residential _{t-1}					-0.003	(0.013)
Human Caused					-0.354	(0.630)
WUI Interface					-0.012	(0.550)
WUI Intermix					-0.007	(0.466)
County Roads					-7.857	(0.171)
Constant					4.597	(0.006)
Observations	1874		1228		746	
Fires	274		228		85	
χ^2	184.50	(0.000)	81.27	(0.000)	4400.95	(0.000)
Vuong Test ^c $\sim N(0, 1)$					2.30	(0.011)

*Response resources are cumulative in Structure Damage equation.

^aCosine transform^bOver dispersion parameter in the ZINB model. Significance tests are likelihood ratio.^c H₀: ZINB=standard negative binomial.

land characteristics. All of the coefficients are negative which implies that as the value of the covariate increases, the more likely the observation is described by the negative binomial model and is less likely to be zero.

With the exception of Type 1 Crews, all response resources increase the total expenditure on a wildfire (negative estimate reduces hazard rate and implies higher expected costs). The magnitude of the Helicopter estimate (-0.275) implies that the use of helicopters contribute the most to wildfire cost.³⁴ The estimate on Type 1 Crews implies that highly trained crews may actually reduce net fire costs.

The covariate estimates in the Wildfire Size and Structure Damage equations provide information about the productivity of each resource relative to other resources within the same regression equation. The Type 1 Crew, Helicopter (not significant), and Engine estimates are all positive implying that these resource types reduce fire size. The results imply that Dozers increase fire size (-0.112). However, Dozers and Type 1 and 2 Crews reduce damage to structures (-0.184, -0.001, and -0.126), where sign of the coefficient estimates in a ZINB model carry the conventional interpretation. Furthermore, the magnitude of the estimate on Dozer (-0.184) implies that dozers are the most effective at reducing damage to residential structures. The positive estimate on Helicopter (0.356) implies that a larger number of structures are destroyed when helicopters are committed to fire i .

The second block of coefficient estimates represent the direct impact of threatened structures on wildfire cost, size, and structure damage conditional on response resource allocation. Lagged Thr. Residential is interacted with Log(Med Home Value), WUI Intermixed, and WUI Interface to investigate whether economic or spatial characteristics significantly impact

³⁴Other aircraft are excluded from the model because data is only reported in selected regions and such a systematic removal of observations would bias the parameter estimates.

wildfire outcomes.³⁵ The striking result is the highly insignificant coefficients on Thr. Residential in each model conditional on resource allocation. This result provides support for hypothesis 5. Furthermore, the interaction of Thr. Residential with WUI Intermix suggests that when homes are mixed with dense vegetation, wildfire cost (-0.003), size (-0.008), and damage (0.011) increase (while only statistically significant in the size model). The results of the interaction between Thr. Residential and WUI Interface are opposite in each model, which implies that in the presence of a clear boundary between vegetation and structures, fire managers invest in suppression. The results on Log(Med Home Value) imply that counties with higher median home values face larger (-0.301) and more expensive (-0.999) fires, but sustain less structure damage (-3.371). These results may be due to the use of property taxes to fund firefighting units.

The weather covariates in the second stage hazard regressions represent direct impacts and are consistent with those in the trivariate hazard model in chapter 2. Windspeed increases fire size (-0.016) and cost (-0.016), and the number of structures damaged and destroyed (0.087). In contrast, Temperature and Humidity reduce fire size and cost, but have no statistically significant impact on structure damage.

3.4.3 Discussion

The results of this analysis suggest that weather and threatened residential structures influence wildfire cost, size, and structure damage. Fluctuations in temperature, windspeed, and humidity have small effects on response resource allocation, but still impact wildfire outcomes. In contrast, threatened residential structures impact response resource allocation which then indirectly affect wildfire outcomes. These results complement the analysis in chapter 2, and highlight the importance of modeling endogenous resource allocation

³⁵Log(Med Home Value), WUI Intermixed, and WUI Interface are time-invariant covariates that were omitted from the response resource allocation equations, and thus represent indirect effects unaccounted for by the inclusion of the instrumented response resource covariates.

throughout the course of a wildfire.

The response resource covariates also provide important information about the productivity of resources used throughout the response effort. One of the most striking results is the high cost, but relatively ineffective, use of helicopters in either suppression or protection effort. These results suggest that if response costs are actually important to wildfire management officials, a critical evaluation of helicopter use should be a priority. The results also suggest that dozers and type 2 crews are among the most productive resources to engage in structure protection, while type 1 crews and engines are adept at mitigating fire growth. This result may be due to the relatively low response time, and high level of training of type 1 crews and engines.

Of the several control covariates, Private Management and State Management contain information relevant to a policy discussion. Privately-managed fires are smaller than federally-managed fires, which is to be expected since there is no private benefit to letting a wildfire burn. State-managed fires are smaller, but more expensive and have significantly less structure damage than federally-managed fires; however, state-managed fires significantly reduce the damage to structures.

The ICS-209 data used in this analysis is an invaluable resource to researchers because it provides a summary of environmental and economic conditions that impact response resource allocation and wildfire outcomes throughout the course of a fire. However, poor quality control of data entry renders many of the observations unusable. While data limitations restrict the sample size, there is no reason to believe that data are missing in any systematic way that would bias regression estimates. The consequence of the restricted sample is evident in the high standard errors (and low statistical significance of estimates) in the second-stage hazard regression estimates.

Throughout this analysis, I assume that both the individual fire manager and regional command unit have complete information, and thus truthfully communicate the marginal

benefit of an additional resource. One may also imagine a scenario in which the regional command unit managing a large number of fires has incomplete information about the marginal benefit of committing resource j to fire i . Individual fire managers may have the incentive to “overstate” their need for resources if doing so allowed them to complete their objectives and possibly receive a promotion. On the other hand, a fire manager might want to prolong a management effort if paid hourly or receives over time benefits.

3.5 Conclusion

I extend the model of wildfire response proposed in chapter 2 to distinguish between individual fire managers and a regional command unit that allocates response resources between fires. I derive a set of estimable resource allocation equations used to quantify the impact of weather and threatened assets on the number of resources committed to a particular fire. These regressions provide information on the factors that influence response resource allocation over the course of a wildfire. In addition, the results are used to generate instruments for the number of resources committed to a particular fire in a second stage regression of wildfire cost, size, and structure damage.

The results suggest that threatened residential structures are a top priority to wildfire management at all levels and receive significantly more response resources than fires without threatened residential structures. The effect of threatened residential structures on wildfire cost occurs primarily through the indirect channel of response resource allocation. Furthermore, the two resources (Type 2 Crews and Dozers) increased when residential structures are threatened, increase fire size and cost suggesting that an increase in the number of threatened residential structures causes a reallocation of resources from suppression toward protection, which increases wildfire cost and size, but reduces structure damage.

These results provide the strongest evidence to date on the impact of the growing wildland

urban interface on wildfire costs. As long as wildfire protection is provided as a public government service, homeowners and developers do not internalize the full cost of building and owning a home in the WUI. Policy-makers should recognize the pressure they impose on wildfire management when designing policies that may facilitate the growth of the WUI while simultaneously cutting budgets. These results also support policies, such as the fire prevention fee recently implemented in California, that impose a fee on homeowners in WUI land under the protection of state and federal firefighting agencies (CABOE, 2013).

Chapter 4

Entry Policy as Indirect Environmental Policy

4.1 Introduction

Growing concern over pollution and climate change have prompted government intervention in energy production. Governments promote renewable energy with a variety of subsidy instruments. European nations offer feed-in tariffs to those who generate energy from renewable sources, i.e., solar and wind. Direct capital subsidies for large-scale solar installations are available in many developed countries including the U.S (IEA, 2011). However, governments often face political opposition to policies designed to promote renewable energy, especially during periods of low economic growth (Stokes, 2013). In such cases, governments may offer grants or low-interest loans to new firms, or simply reduce the administration costs of firm entry as a form of indirect environmental policy.

Governments must also recognize the implications of domestic entry policy on the market structure of the regulated industry. When firms located in regions subject to different entry policies compete in a global market, the optimal domestic entry policy depends on the policies in other regions.¹ Given the global nature of many product markets, the following questions arise: How do domestic entry policies impact firm entry in imperfect globally competitive markets? Do governments have the incentive to strategically set entry policy?

The objective of this paper is to characterize the conditions under which competing governments use entry policy as an indirect form of environmental policy, and to analyze the

¹Golombek and Hoel (2011) highlight this point in an analysis of R&D subsidies for climate-friendly technology in an international context.

subsequent welfare implications of such policies. I develop a model of strategic entry policy in which regulators located in two different regions set entry taxes, subsidies, or permit restrictions to deter or attract entry of firms that will subsequently compete in a Cournot oligopoly.

I show that the existence of a rival regulator precludes the socially optimal level of entry, which leads to suboptimal welfare. Furthermore, equilibrium outcomes may differ dramatically under price and quantity policies. If competing governments are restricted to price-based entry policies (i.e., taxes and subsidies), the game structure is analogous to Bertrand competition and entry taxes become ineffective while entry subsidies are provided in only one of the two regions. If governments use quantity policies, the game structure is analogous to Cournot competition and a subset of optimal outcomes are attainable.

Over the past several decades, the WTO has actively discouraged countries from using strategic trade policies to promote the competitiveness of firms within their jurisdiction. As environmental policy has gained acceptance, concern over the strategic use of environmental policy has grown (Whalley, 1991; Barrett, 1994; Bayındır-Upmann, 2003). A large literature has since analyzed the strategic use of emission standards and fees and the subsequent welfare impacts of such policies. While this literature has considered environmental policies under both exogenous and endogenous market structures, no studies have analyzed the strategic use of entry policies in an multi-region open economy under an endogenous market structure.

This paper lies at the intersection of a literature on strategic environmental and trade policy, and tax competition. The early literature on strategic trade policy demonstrates that governments may promote the competitiveness of domestic firms in imperfectly competitive international markets with R&D subsidies (Spencer and Brander, 1983) export subsidies (Brander and Spencer, 1985), import tariffs (Brander and Spencer, 1981) and domestic taxes and subsidies (Eaton and Grossman, 1986). Barrett (1994), Ulph (1996), and Kennedy (1994), among others, then extended the analysis to include environmental policy in an

open economy. The common theme in this literature suggests that governments may adopt environmental policies in an open economy that would be suboptimal in a closed economy.

Several studies have since extended the literature on strategic environmental and trade policy to include endogenous entry in response to changes in policy (Katsoulacos and Xepapadeas, 1995; Bhattacharjea, 2002; Greaker, 2003; Bayındır-Upmann, 2003; Fujiwara, 2009; Haufler and Wooton, 2010; Etro, 2011). Katsoulacos and Xepapadeas (1995) shows that under endogenous entry, the optimal emission fee is in excess of marginal external damage to mitigate the social inefficiency due to excessive entry. Cato (2010) develops a three-part instrument that includes a license fee that may be positive or negative. Bayındır-Upmann (2003) argues that governments may weaken environmental regulation to indirectly support domestic firms in a globally competitive environment with endogenous entry. This literature focuses almost exclusively on pollution externalities in production and the emission fees and standards used to control them. In contrast, I investigate environmental policies in the presence of external benefits from goods that reduce pollution.

In a closely related literature on tax competition, rival governments compete over the foreign direct investment and associated tax revenue from domestically located firms. Competition between governments occurs through the relaxation of regulation (Zodrow and Mieszkowski, 1986; Wilson, 1999). Mintz and Tulkens (1986) characterizes a non-cooperative fiscal equilibrium in multi-region model where tax rates are the strategic variable and governments seek to raise revenue to fund public goods. Janeba (1998) develops a two-region model in which firms selling a homogeneous good to a third market choose to locate in the region with the lowest cost. As in this paper, the lack of transportation costs implies that governments face large discontinuities (due to aggregate firm profits) when setting tax policy in a globally competitive environment. Markusen, Morey, and Olewiler (1995) studies the mechanism driving this welfare discontinuity with a model of firm location in which negative pollution externalities are regulated by governments two regions. The model developed

in this study also exhibits welfare discontinuities that prevent the attainment of mutually beneficial outcomes.

Entry subsidies have been studied in the context of differentiated products where consumers desire variety (DeRemer, 2011; Pflüger and Südekum, 2013), but have received little attention in models of homogeneous goods.² One notable exception is Reitzes and Grawe (1999) who develop a two-country model to analyze the optimal entry policy under a variety of scenarios. Their analysis of entry policies is unique because they assume an existing number of incumbent firms in both countries and characterize the conditions under which entry taxes or subsidies are welfare improving in the home country. In contrast, this study considers a purely endogenous market structure in which two regulators strategically choose entry policy in open economies with positive environmental externalities.

The chapter is organized as follows. Section 4.2 establishes the unregulated and regulated equilibrium in a single exporting region. Section 4.3 extends the model to account for inter-regional competition in a two-region economy. Section 4.4 compares the welfare outcomes of the single- and two-region case and highlights the impact of interregional competition on entry policy. Section 4.5 discusses the policy implications of the model and concludes the paper.

4.2 Single Region

Consider a complete information model of oligopoly where firms sell a homogenous product domestically and abroad. Each firm $i = 1, \dots, n$ faces an inverse demand $P(Q) = a - bQ$ where Q denotes total output. Output is either sold domestically, $Q^A = \gamma Q$, or in a foreign market, $Q^B = (1 - \gamma)Q$ where γ denotes the share of output sold domestically. In this section, all output is produced by domestic firms. Firms are identical in their technology

²Mankiw and Whinston (1986) develops a simple model of imperfect competition with endogenous entry to show that privately optimal entry is not socially optimal when fixed entry costs exist.

with a constant marginal cost of production, c , where $a > c \geq 0$ ensures that the first unit of output will be produced. Conditional on the number of firms in the market, n , each firm earns post-entry profits of

$$\pi_i(n) \equiv \frac{(a - c)^2}{b(n + 1)^2}.$$

As a benchmark for comparison, I first identify the equilibrium number of firms when regulation is absent (referred to as the unregulated equilibrium), and in the following subsection I examine the optimal number of firms from the regulator's perspective (referred to as the regulated equilibrium).

4.2.1 Unregulated Equilibrium

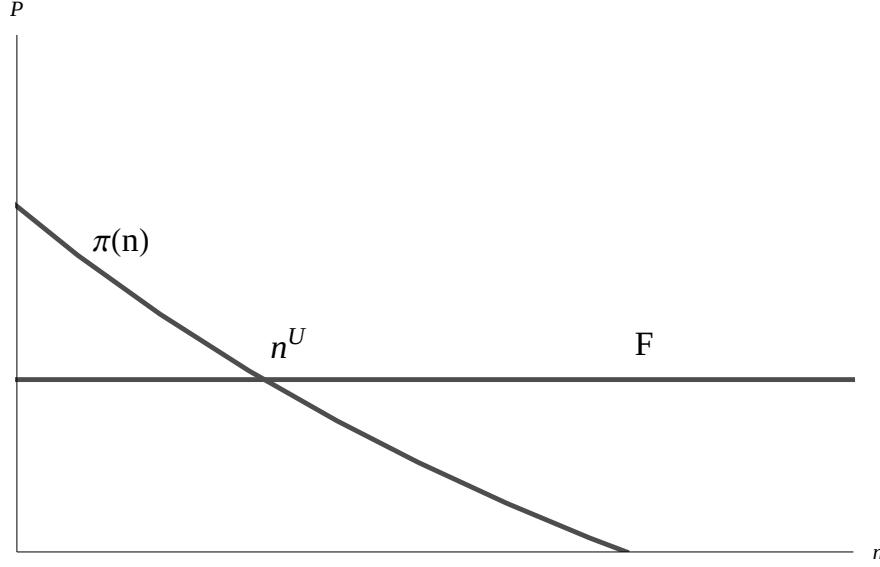
Upon entry, firms pay a fixed irrecoverable cost $F > 0$ that represents industry specific research and development necessary to enter the market. Therefore, a firm i enters if $\pi_i(n) - F \geq 0$. In order to guarantee the entry of at least one firm, I assume that the fixed entry cost is not prohibitive, i.e., $\pi_i(1) \equiv F_{max} \geq F$. The unregulated level of entry is given by the following lemma.

Lemma 1. *The unregulated equilibrium number of firms, n^U , solves $\pi_i(n) = F$ and is given by $n^U = \frac{a-c}{\sqrt{Fb}} - 1$*

Figure 7 depicts the result of lemma 1, where profits of the representative firm decrease in the number of competing firms.³ Equilibrium profits, $\pi(n)$, shift upward as a increases, which increases n^U as a consequence; and shift downward in b and c , which decrease n^U . Similarly, an increase in F reduces the equilibrium number of firms, n^U .

³The parameters chosen to generate figure 7 are $a = 2, b = 1$, and $c = .1$ for $n \geq 1$. Other parameters yield similar results and can be provided by the authors upon request.

Figure 7: The unregulated equilibrium number of firms.



4.2.2 Regulated Equilibrium

Entry in the unregulated equilibrium is not necessarily optimal from the domestic regulator's perspective. While a potential entrant may find it profitable to enter, it competes for market share with, and erodes the profits of, incumbent firms. In this section, I introduce a regulator that can choose the number of market entrants in order to maximize the domestic welfare function⁴

$$W(n) \equiv \gamma CS(Q(n)) + \sum_i^n \{\pi_i(n) - F\} + D(Q^A(n)), \quad (4.1)$$

where CS is total consumer surplus and $D(Q^A(n)) = dQ^A(n)$ is the external benefit of reduced pollution (and d is the marginal external benefit).⁵ The following lemma identifies

⁴To demonstrate why the planner's direct choice of n is equivalent to an indirect entry policy that alters the fixed entry cost, consider an alternative welfare function: $W(n) \equiv \gamma CS(Q(n)) + \sum_i^n \{\pi_i(n) - (F + z)\} + nz + D(Q^A(n))$ where z is the entry tax or subsidy, and $\sum_i^n z = nz$. This welfare function simplifies to $W(n) \equiv \gamma CS(Q(n)) + \sum_i^n \{\pi_i(n) - F\} + D(Q^A(n))$, and thus is equivalent to (4.1).

⁵This external benefit arises from a substitution away from polluting goods. In the case of energy, d represents the marginal benefits of using renewable energy instead of carbon-based fuels, i.e., coal and petroleum.

the welfare-maximizing number of firms.⁶

Lemma 2. *The regulated equilibrium number of firms, n^R , maximizes domestic welfare and solves the first-order condition*

$$\gamma \frac{\overbrace{n\gamma(a-c)^2}^{CS_n(n)}}{b(n+1)^3} + \frac{\overbrace{(a-c)^2}^{\pi_i(n)-F}}{b(n+1)^2} - F + \frac{\overbrace{d}^{D_n(n)}}{2} \left(\frac{\gamma d(a-c)}{b(n+1)^2} \right) = 2n \frac{\overbrace{(a-c)^2}^{n\pi_{in}(n)}}{b(n+1)^3}. \quad (4.2)$$

The left hand side of equation (4.2) represents the domestic benefit of an additional entrant including the increased consumer surplus due to a larger aggregate output, $CS_n(n)$, the net profits of the new entrant, $\pi_i(n) - F$, and the external benefits associated with an increase in domestic consumption, $D_n(n)$. Each of these three terms is positive, but diminishing in n . In contrast, the right hand side of the first order condition represents the domestic social marginal cost of entry, namely, the dissipation of aggregate profits that incumbents experience after the entry of a new firm. The domestic social marginal cost is positive and decreasing in n . Figure 8 depicts the domestic social marginal benefits and cost as a function of the number of firms, n .⁷ Hence, the regulated number of firms, n^R , occurs at the point where the domestic social marginal benefits of an additional firm, $SMB(n)$, coincide with the associated domestic social marginal cost, $SMC(n)$.⁸ For comparison, the figure also illustrates the net profit, $\pi_i(n) - F$, which a firm considers in its private entry decision, which yields the unregulated number of firms, n^U , when $\pi_i(n) - F = 0$.

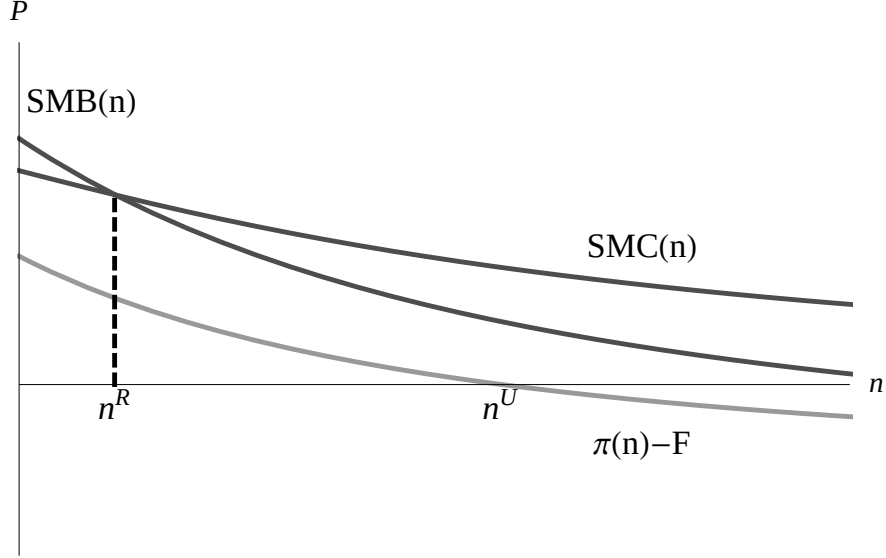
The domestically optimal level of entry, n^R , may differ from the privately optimal level of entry, n^U . In this case, the regulator can utilize an entry policy to induce the domestically optimal level of entry. In particular, the regulator may set a tax, z , which solves $\pi(n^R) = F + z$, where $z > 0$ as long as private entry exceeds the domestic optimum, $n^U > n^R$,

⁶The subscripts denote partial derivatives.

⁷For consistency, figure 8 also considers the same parameter values as in figure 7, i.e., $a = b = d = \gamma = 1$, $F = .2$, and $c = 0$ for $n \geq 1$.

⁸Since the domestic welfare function is locally concave in n , a unique equilibrium for n^R exists. See appendix C.2

Figure 8: Regulator's marginal cost and benefit curves along with the firm's profit less entry cost.



ultimately deterring firms from entering into the industry. This occurs, for instance, when no external benefit arises from the domestic consumption of the good, i.e., $d = 0$, which is consistent with the results in Mankiw and Whinston (1986).⁹ Alternatively, the regulator may require a permit to enter and operate, and only make n^R permits available. Because the tax policy amounts to a revenue neutral transfer, both policies are equivalent in the single-region economy. When private entry is below the domestic optimum, $n^U < n^R$, as in figure 8, the regulator may set an entry subsidy $z < 0$, which again solves $\pi(n^R) = F + z$. Such a policy creates the incentive for additional firms to enter the market.¹⁰

Lemma 3 compares the unregulated and regulated equilibrium number of firms showing that the former exceeds the latter when the domestic social marginal cost of entry exceeds

⁹Mankiw and Whinston (1986) demonstrate that social inefficiency arises when an additional entrant erodes the profits of incumbent firms to a greater extent than the additional social benefit this firm brings, captured by the increase in aggregate output.

¹⁰In this case, the permit policy is immaterial because even if the number of permits available is increased, firms do not enter because they would earn negative profits. In addition, note that this model assumes that all firms are homogeneous in technology. If firms are heterogeneous in technology, some inefficient firms exist, and entry subsidies may promote their entry, thus generating a welfare loss (Pflüger and Südekum, 2013; Santarelli and Vivarelli, 2002).

the domestic social marginal benefit of entry at the unregulated equilibrium.¹¹

Lemma 3. *The privately optimal level of entry exceeds the domestically optimal level of entry, $n^U > n^R$, if and only if $n\pi_n(n^U) > \gamma CS_n(n^U) + D_n(n^U)$, or alternatively, when the external benefit is sufficiently low, i.e., $d < \bar{d}$ where*

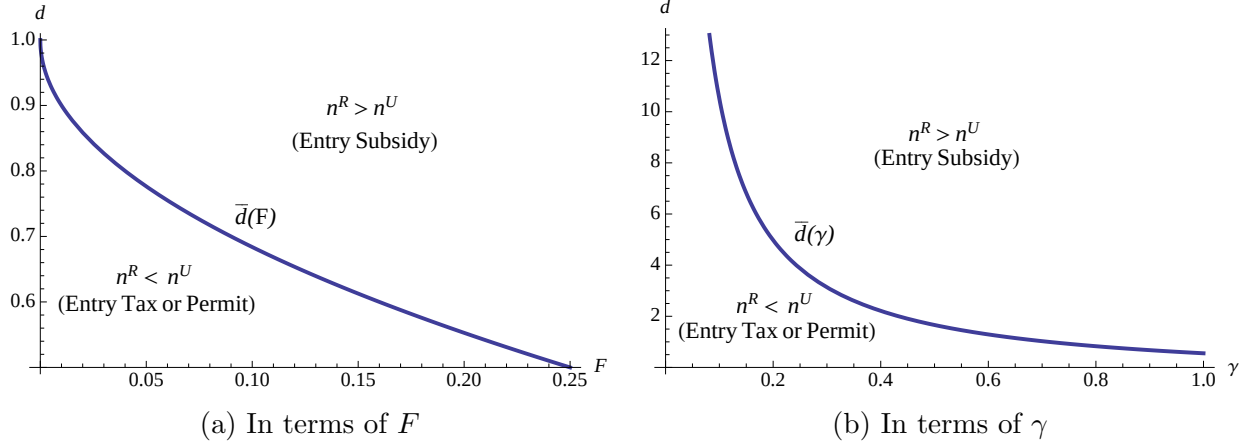
$$\bar{d} \equiv \left(\frac{2}{\gamma} - 1 \right) (a - c - \sqrt{Fb})$$

Hence, when $d < \bar{d}$, entry is excessive, $n^U > n^R$, and the regulator must implement entry taxes; as in Mankiw and Whinston (1986) who focus on the case in which $d = 0$. In contrast, if $d \geq \bar{d}$, entry is insufficient from the regulator's point of view, $n^U < n^R$, the regulator must implement an entry subsidy. Figure 9a illustrates the cutoff, $\bar{d}$, as a function of the fixed entry cost, F , while figure 9b depicts it as a function of the share of domestic consumption, γ .¹² Given the chosen parameter values in panel a, (F, d) pairs below $\bar{d}$ would imply an entry tax, $z > 0$, which induces the domestically optimal number of entrants, n^R (or the allocation of a fixed number of permits, n^R), whereas those (F, d) pairs above $\bar{d}$ would imply an entry subsidy, $z < 0$. As the fixed cost of entry rises, firm profits fall, which curtails both private and domestically optimal entry. However, the domestic social marginal benefit decreases at a lower rate than private marginal benefits. Panel b illustrates the impact of the domestic sales on the external benefit threshold, $\bar{d}(\gamma)$. Intuitively, the regulator is more willing to subsidize entry as the share of domestic consumption rises. Specifically, as a larger share of output is consumed domestically, both consumer surplus and the external benefit (which depend on the quantity consumed) increase. As a consequence, insufficient entry occurs under a larger set of (γ, d) pairs.¹³

¹¹See appendix for proof.

¹²I continue with the parameter values in figure 8: $a = b = \gamma = 1$ and $c = 0$ for $F \in [0, F_{max}]$ where $F_{max} = \frac{(a-c)^2}{4b} = \frac{1}{4}$. F_{max} is the entry cost that would prevent all but one entrant.

¹³Note that when $\gamma = 1$, the economy is effectively closed to trade, as in Katsoulacos and Xepapadeas (1995). However, in contrast to Katsoulacos and Xepapadeas (1995) where production generates external

Figure 9: Cutoff for parameter d , $\bar{d}$, above which z is a subsidy.

4.3 Two-Region Economy

I now extend the model to include two regions. When firms operating under separate jurisdictions compete for market share, regulation of one set of firms can impact welfare in other jurisdictions. Therefore, each regulator anticipates the actions of the rival regulator when choosing its welfare maximizing policy.

Firms in each region are subject to separate entry regulation. All agents are fully informed. Consider x firms operating in region A , and y firms operating in region B . Firms are still homogeneous in technology within and between regions as factors of production are freely mobile between regions. The cost of production, c , is symmetric across regions.¹⁴ The fixed entry cost is allowed to differ between regions A and B , denoted F^A and F^B , respectively. All firms face the same global demand curve defined in section 4.2, a proportion of which (γ) is sold in region A , while the remaining share ($1 - \gamma$) is sold in region B .

Firms in each region simultaneously choose output to maximize profits given the behavior of other firms within the region and those operating within the other jurisdiction. Since firms

costs, consumption generates additional benefits in this model, which leads the regulator to favor further entry when these benefits satisfy $d > \bar{d}$, but hinder entry otherwise.

¹⁴In addition, production cost is invariant to regional destination of output as in Janeba (1998) and Bayındır-Upmann (2003).

are symmetric, the equilibrium output of each firm $i = 1, \dots, x + y$ now depends not only on the number of firms in its own region, x , but also on those in a foreign region, y .

$$q_i^k(x, y) = \frac{a - c}{b(1 + x + y)} \quad \text{for } k = A, B$$

The equilibrium output of each firm is decreasing in the number of competing firms, $x + y$, regardless of their location. The equilibrium profits of a representative firm located in any region $k = \{A, B\}$ are $\pi^k(x, y) = \frac{(a-c)^2}{b(1+x+y)^2}$, which are also decreasing in the number of entrants.¹⁵

In a format similar to section 4.2, I first examine the equilibrium number of firms when regulation is absent (unregulated equilibrium), then analyze the regionally optimal number of firms in the regulated equilibrium.¹⁶

4.3.1 Two-Region Unregulated Equilibrium

Since this model does not consider transportation costs and consumers perceive the goods to be perfect substitutes, firm location is uniquely determined by the fixed entry cost. If entry costs are lower in region A than region B , all firms would enter in region A and vice versa. If the entry cost is equal between countries A and B , firms are indifferent between operating in either region. The following lemma confirms this result.

Lemma 4. *Firm i enters market $k = \{A, B\}$ if $\pi_i^k(x, y) - F^k > \pi_i^\ell(x, y) - F^\ell$, where $k \neq \ell$, and is indifferent between entering either if $\pi_i^k(x, y) - F^k = \pi_i^\ell(x, y) - F^\ell$. Hence, the unregulated equilibrium number of entrants in regions A and B solves $\pi_i^k(x, y) - F = 0$ and*

¹⁵In addition, note that individual profits rise as demand increases (higher a) or becomes less elastic (lower b), and fall as own production costs, c , increase.

¹⁶Regionally optimal refers to the number of firms that each regions' regulator would induce conditional on the number of firms that the rival regulator would induce.

is given by the (x, y) -pair

$$(x^U, y^U) = \begin{cases} x = n^U, y = 0 & \text{if } F^A < F^B \\ (x, y) \text{ s.t. } x + y = n^U & \text{if } F^A = F^B \\ x = 0, y = n^U & \text{if } F^A > F^B \end{cases} \quad (4.3)$$

When the entry costs are symmetric across regions (i.e., $F^A = F^B$), every (x, y) -pair that satisfies $x + y = n^U$ is a possible equilibrium. For simplicity, I focus on the symmetric equilibrium in which $x^U = y^U = \frac{1}{2}n^U$, where $n^U = \frac{a-c}{\sqrt{bF}} - 1$. In contrast, when entry costs are lower in one country, all n^U firms enter that region.

4.3.2 Two-Region Regulated Equilibrium

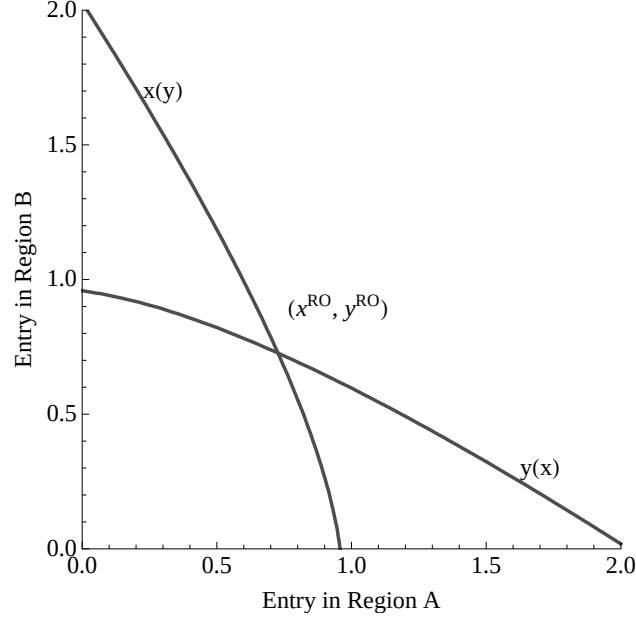
I now characterize the regionally optimal level of entry in each region. If every regulator could choose the number of firms within its jurisdiction conditional on the number of firms in the rival region, they would solve

$$\max_x W^A(x, y) \equiv \gamma CS(Q(x, y)) + x(\pi^A(x, y) - F) + D^A(Q^A(x, y)) \quad (4.4)$$

$$\max_y W^B(x, y) \equiv (1 - \gamma)CS(Q(x, y)) + y(\pi^B(x, y) - F) + D^B(Q^B(x, y)) \quad (4.5)$$

where total output is now defined as $Q = xq^A + yq^B$, with $Q^A = \gamma Q$ sold in region A , and $Q^B = (1 - \gamma)Q$ sold in region B . Production costs, c , and the external benefit of domestic consumption, d , are assumed to coincide across countries.¹⁷ The first-order conditions of regulator A and B equate the marginal social benefits with the marginal social costs of

¹⁷Bayındır-Upmann (2003) circumvents the complication of two regions who simultaneously use policy in order to achieve a regionally optimal level of entry by assuming that the number of foreign firms is exogenous. Unlike this paper, that approach neglects the response of each regulator to the others' policy.

Figure 10: The regulators' best response functions in regions A and B .

within-region entry.

$$[\text{Region } A] \quad \gamma CS_x(x, y) + \pi^A(x, y) - F + D_x^A(x, y) = x\pi_x^A(x, y) \quad (4.6)$$

$$[\text{Region } B] \quad (1 - \gamma)CS_y(x, y) + \pi^B(x, y) - F + D_y^B(x, y) = y\pi_y^B(x, y) \quad (4.7)$$

The first-order conditions implicitly characterize the regulator's best response functions, $x(y)$ and $y(x)$, which are illustrated in figure 10.¹⁸ Region A 's best response function is decreasing in y . The shape of the best response functions suggests that regulator A perceives entry in region B as a strategic substitute for domestic entry. Despite the erosion of profits by firms in region A , entry in region B provides benefits to consumers in region A . In particular, as entry in the foreign region increases, aggregate domestic output increases, which contributes to the marginal benefit domestically through consumer surplus and the external benefit of reduced pollution. The best response function of region A , $x(y)$, shifts outward as the share of region A 's consumption, γ , increases. Intuitively, for a given number of foreign firms, the

¹⁸For consistency, I continue using parameter values: $a = b = d = 1$, $c = 0$, $F = 0.2$, and now assume that each region consumes half of total production (i.e., $\gamma = 0.5$).

regulator in region A would optimally induce a larger number of firms as γ increases. Since both regions share the same external benefit of domestic consumption, an increase in the external benefit of consumption, d , shifts each region's best response function outward at the same rate, which results in a proportional increase in the total level of entry in both regions.

The intersection of the best response functions in figure 10 indicates the preferred level of entry in each region under regulation. If both regulators can induce x^{RO} and y^{RO} using entry policy, then the intersection becomes a candidate for the two-region regulated equilibrium.

Pecuniary Externalities of Entry

Entry in region $k = \{A, B\}$ creates pecuniary externalities on region $\ell \neq k$ that arise from the regulator in each region maximizing domestic welfare within its own jurisdiction, without taking into account the effect that further entry in the domestic industry has on foreign firms' profits. The pecuniary externality is defined by comparing the first-order conditions of each regulator (in equations (4.6) and (4.7)) and a hypothetical regulator with jurisdiction over both regions. The single-region regulator developed in section 4.2.2 provides a convenient representation of the two-region social planner when all consumption is domestic ($\gamma = 1$), i.e., an international coordinator of entry policies that maximizes aggregate social welfare across both regions. The two-region regulator's problem is¹⁹

$$\max_{x,y} W(x,y) \equiv W^A(x,y) + W^B(x,y) \quad (4.8)$$

¹⁹Concavity of the social welfare functions W^A and W^B implies that the joint welfare function $W \equiv W^A + W^B$ is also concave.

where $W^A(x, y)$ and $W^B(x, y)$ are defined in equations (4.4) and (4.5), respectively. The first-order conditions of the cross-region regulator are

$$[x] \quad \gamma CS_x + (\pi^A - F^A) + x\pi_x^A + D_x^A + \overbrace{(1 - \gamma)CS_x + D_x^B + y\pi_x^B}^{\text{pecuniary externality}} = 0 \quad (4.9)$$

$$[y] \quad (1 - \gamma)CS_y + (\pi^B - F^B) + y\pi_y^B + D_y^B + \overbrace{\gamma CS_y + D_y^A + x\pi_y^A}^{\text{pecuniary externality}} = 0. \quad (4.10)$$

The (x, y) -pair that solves (4.9) and (4.10) must also satisfy $x + y = n^R$ where n^R is the regulated number of firms defined in lemma 2 for $\gamma = 1$.

The pecuniary externality is comprised of a positive and negative component. On one hand, a larger number of domestic firms increases domestic production, thus entailing a larger foreign consumption of domestic products. In turn, this increases both the foreign consumer surplus and the external benefits that the foreign economy experiences from such additional consumption. On the other hand, however, a larger number of domestic firms also imposes a negative pecuniary externality on the foreign country, since foreign firms now face tougher competition.

Lemma 5 specifies the conditions under which the positive pecuniary externalities of regulator A on regulator B dominate the negative.

Lemma 5. *Entry in region A creates a positive pecuniary externality on region B if $(1 - \gamma)CS_x + D_x^B > -y\pi_x^B$.*

These pecuniary externalities of entry alter the external benefit cutoff $\bar{d}$ defined in lemma 3. Lemma 6 defines an analogous external benefit cutoff for the two-region case.

Lemma 6. *The regionally optimal level of entry exceeds the privately optimal level of entry in region A , $x^{RO} > x^U$ (in region B , $y^{RO} > y^U$), if and only if $W_x^A(x^U, y^U) > 0$ ($W_y^B(x^U, y^U) > 0$, respectively), or alternatively, when the external benefit is sufficiently high, i.e., $d^A > \underline{d}^A$*

for region A and $d^B > \underline{d}^B$ for region B , where

$$\underline{d}^A \equiv \frac{b(1-\gamma)}{\gamma} (a - c - \sqrt{Fb}); \quad \text{and} \quad \underline{d}^B \equiv \frac{b\gamma}{1-\gamma} (a - c - \sqrt{Fb})$$

Figure 11 depicts cutoffs $\underline{d}^A$ and $\underline{d}^B$ as a function of the share of domestic consumption, as well as the social planner's cutoff, d^{SO} . The planner's cutoff is constant in the share of consumption because regional consumption is irrelevant to aggregate consumer surplus.²⁰ Cutoffs $\underline{d}^A$ and $\underline{d}^B$ are inversely related through their respective shares of domestic consumption (γ in region A and $1 - \gamma$ in region B) and divide the parameter space (γ, d) into four partitions that characterize each regulators entry preferences for any share of consumption and external benefit. Partition (1) represents the parameter space in which both regulators would prefer to induce entry beyond the unregulated equilibrium ($x^{RO} > x^U$ and $y^{RO} > y^U$), since the external benefits of consumption are large in both regions.²¹ In Partition (2), regulator A would prefer to encourage entry ($x^{RO} > x^U$) while regulator B would prefer to discourage entry ($y^{RO} < y^U$), given that $\underline{d}^B > d > \underline{d}^A$. Intuitively, region A is benefiting more from consumer surplus and external benefits than firm profits. Partition (2) is bisected by the social planner's parameter cutoff. In (2a), the social planner would encourage entry in excess of the unregulated equilibrium, whereas (2b) the planner would deter entry. The opposite is true in partition (3) where only regulator B would encourage entry ($y^{RO} > y^U$). Finally, in partition (4), both regulators would prefer to discourage entry ($x^{RO} < x^U$ and

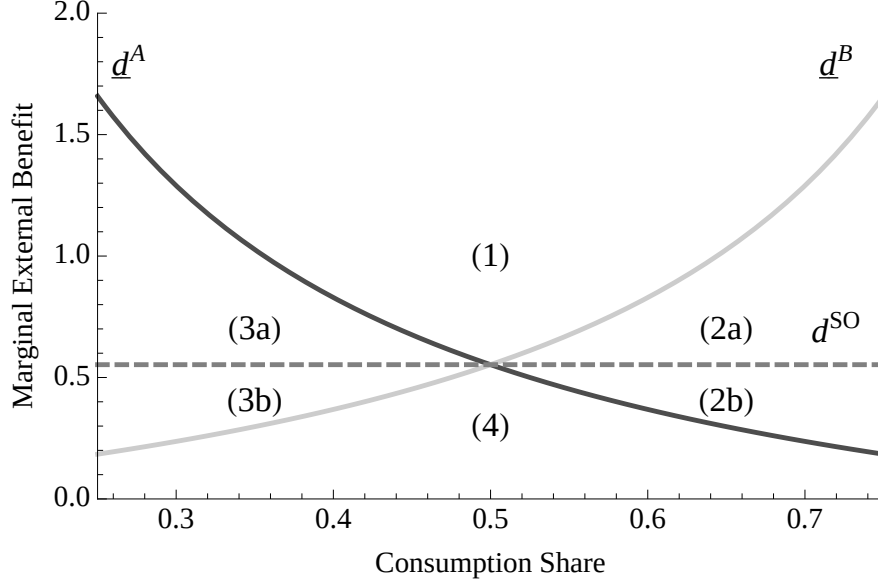
²⁰The planner's external benefit cutoff, above which he would prefer to induce entry, is

$$d^{SO} = \bar{d}(\gamma = 1) = (a - c - \sqrt{Fb}).$$

The two-region cutoffs can be restated in terms of the planner's cutoff as $\underline{d}^A \equiv \frac{b(1-\gamma)}{\gamma} d^{SO}$ and $\underline{d}^B \equiv \frac{\gamma}{b(1-\gamma)} d^{SO}$. This implies that the relationship between the two-region cutoffs and the planner's cutoff depends on the demand elasticity and the share of domestic consumption in regions A and B . Intuitively, as demand becomes more elastic (b decreases), more entry occurs without regulation because monopoly rents rise, which reduces the individual regulator's need to provide subsidies. The planner's cutoff d^{SO} only intersects $\underline{d}^A$ and $\underline{d}^B$ at $\gamma = 0.5$ when $b = 1$.

²¹Recall that because there are no transportation costs, the unregulated equilibrium (x^U, y^U) is independent of γ .

Figure 11: Cutoffs for parameters d^A and d^B , above which a regulator would encourage entry.



$y^{RO} < y^U$), since the external benefits of consumption are relatively low in both regions.

4.3.3 Policies in Two-Region Economy

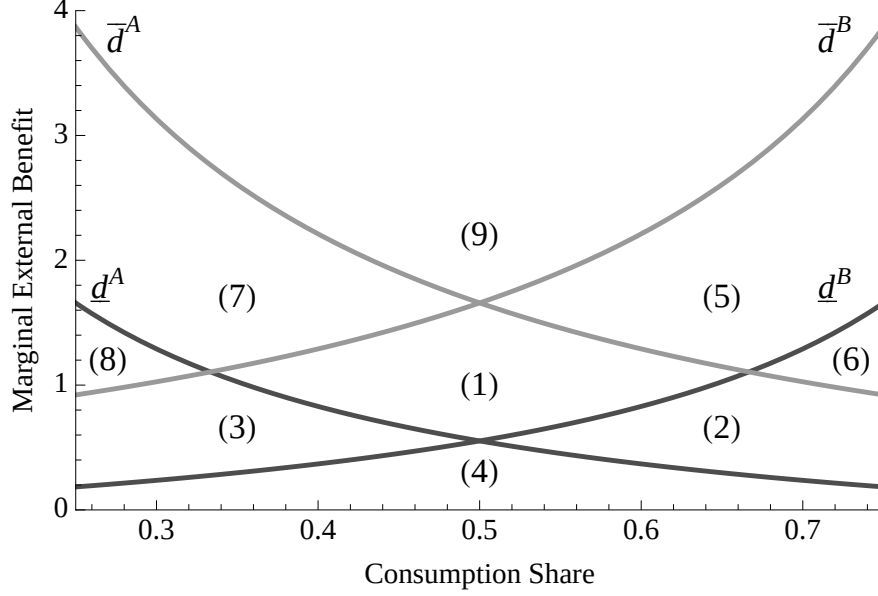
Until now I have taken the regulators ability to induce the regionally optimal level of entry as a given. I now analyze whether (x^{RO}, y^{RO}) is an attainable equilibrium under a price-based entry policy (i.e., entry tax or subsidy) and a quantity-based policy (i.e., entry permits, licenses, quotas). It will be instructive to superimpose the single-region regulated equilibrium curves, i.e., cutoffs $\bar{d}^A$ and $\bar{d}^B$, onto figure 11, which divides the parameter space into nine partitions.²²

Assumption 1. *The distance between $\bar{d}^k$ and $\underline{d}^k$ for $k = \{A, B\}$ depends on the slope of the demand function b . I assume that $b < \frac{2-\gamma}{1-\gamma}$ to ensure that $\bar{d}^k$ lies above $\underline{d}^k$ for $k = \{A, B\}$.*

The single-region cutoff denoted $\bar{d}^A(\gamma)$ in figure 12 is identical to the curve, $\bar{d}(\gamma)$, depicted in figure 9b. Since regions A and B are symmetric, the cutoff $\bar{d}^B(\gamma)$ is the reflection of $\bar{d}^A(\gamma)$

²²Assumption 1 ensures that partitions (1), (5), and (7) exist.

Figure 12: Partitions characterizing the two-region regulated equilibrium.



over $\gamma = 0.5$. Partitions (1)-(4) carry the same interpretations in figure 12 as they do in 11.

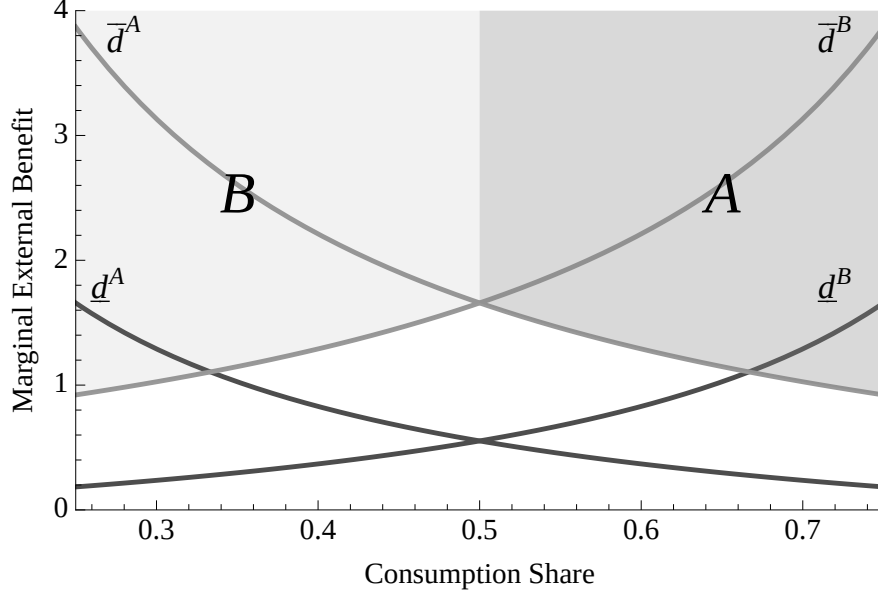
Partitions (5) and (6) represent the parameter space for which regulator A would subsidize entry regardless of regulator B 's strategy. Intuitively, the external benefits are high enough in partitions (5) and (6) that despite exporting output to region B , the benefits of entry in region A are larger than the negative net profits incurred by subsidizing entry beyond the unregulated equilibrium level of entry ($n^R > n^U$).²³ By symmetry, the same results hold in partitions (7) and (8), but the regulator's roles are reversed. In partition (9), the external benefit lies above both $\bar{d}^B(\gamma)$ and $\bar{d}^A(\gamma)$, which implies that both regulators would be willing to subsidize entry regardless of its rivals policy choice.

Price-Based Entry Policy

I first consider the case where both regulators attempt to induce the regionally optimal level of entry with a price-based entry policy.

²³In partition (6), regulator B would prefer to restrict entry because the relative welfare gains from additional profit are larger than those from external benefit and consumer surplus. In partition (5), regulator B would subsidize entry to induce the regionally optimal output y^{RO} , but would not bear the cost of subsidizing all entrants, since $y^{RO} < n^R$ in region B .

Figure 13: Parameter space in which subsidy equilibrium exists.



Proposition 4. *Under a price-based entry policy: both regulators set a tax $z^A = z^B = 0$ and induce the unregulated equilibrium level of entry (x^U, y^U) if $d < \min \{\bar{d}^A, \bar{d}^B\}$; and only regulator A (B) sets a subsidy $z^A(z^B) < 0$ to induce n^R entrants in region A (B) if $d \geq \min \{\bar{d}^A, \bar{d}^B\}$ and $\gamma > 0.5$ ($\gamma < 0.5$).*

Proof. Although both regulators would prefer to impose a tax on entry in partition (4), there exists an incentive to steal entry from the rival. As with firms that compete in a Bertrand duopoly, regulator $k = \{A, B\}$ can undercut the entry price in region $\ell \neq k$ and “steal” the entrants and associated rents. This incentive to steal the entire share of entrants undermines the regulators efforts to achieve the regionally optimal level of entry. Therefore, both regulators set an entry fee $z^A = z^B = 0$ and the unregulated equilibrium (x^U, y^U) results.²⁴

Partitions (1), (2), and (3) in figure 12 all represent situations in which at least one regulator has the incentive to subsidize entry. However, the welfare gains of subsidization depend on the rival regulator inducing their share of the regionally optimal level of entry.

²⁴Note that when $z^A = z^B = 0$, the price of entry is equal to the marginal cost of entry, F , as in a Bertrand duopoly.

In partitions (2) and (3), one regulator has the incentive to subsidize while the opposing regulator has the incentive to restrict entry. Since all firms choose to locate in the low-cost region, all entry occurs in the subsidizing region. All entry in one region must necessarily reduce welfare since $d \leq \min \{\bar{d}^A, \bar{d}^B\}$ implies that the single-region regulated equilibrium is below the unregulated equilibrium ($n^R < n^U$). In partition (1), both regulators prefer to subsidize entry, but a strong incentive to free-ride prevents the regionally optimal entry outcome. Since one regulator bears the cost of subsidizing entry (negative firm profits), the opposing regulator benefits from the additional output at no welfare cost. Hence, neither regulator subsidizes or taxes entry in partitions (1), (2), and (3) and the unregulated equilibrium results, (x^U, y^U) .²⁵

In partitions (5)-(9), the single-region regulated equilibrium exceeds the unregulated level of entry (i.e., $n^R > n^U$). This case differs from the previously discussed case in that one of the two regulators finds it optimal to subsidize entry. In partitions (5), (6), and (9) ($\gamma > 0.5$), depicted by the darker shaded region in figure 13, regulator A would subsidize entry regardless of regulator B 's policy. In partition (6), regulator B prefers to restrict entry, but all firms would enter into the subsidized region, and any entry tax would be immaterial. In partition (9), both regulators have incentive to simultaneously subsidize entry up to the single-region regulated equilibrium and free ride off of the rival regulator policy. The regulator with the larger share of domestic consumption has slightly more incentive to subsidize entry. By symmetry, regulator B subsidizes entry in the lighter shaded region of figure 13. Therefore, the single region regulated equilibrium, n^R persists in partitions (5)-(9) and the region with the larger share of consumption subsidizes all of the entrants. $\square$

²⁵Espinola-Arredondo and Munoz-Garcia (2011) show that countries abstain from international environmental agreements when there exists a strong incentive to free-ride.

Quantity-Based Entry Policy

I now consider the case in which both regulators are limited to a quantity-based entry policy such as permit restrictions.²⁶

Proposition 5. *Under a quantity-based entry policy: both regulators limit the number of entrants and induce the regionally optimal level of entry, (x^{RO}, y^{RO}) , if $d \leq \min \{\underline{d}^A, \underline{d}^B\}$; and do not limit the number of entrants yielding the unregulated level of entry, (x^U, y^U) , if $d > \min \{\underline{d}^A, \underline{d}^B\}$.*

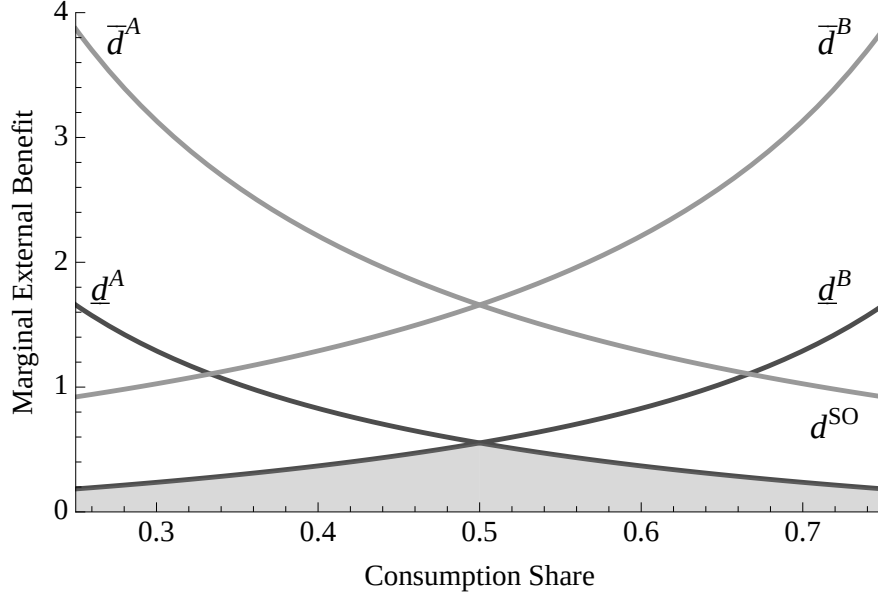
Proof. A permit policy is limited to restricting entry and provides firms no additional incentive to enter when external benefits are high. Another important feature of the permit policy is the lack of entry stealing effect. An increase in the number of permits offered by region A does not induce the firms in region B to relocate where as an increase in a subsidy does. This eliminates discontinuities in the strategy space and results in a structure of competition analogous to a Cournot duopoly.

In partition (4), depicted by the shaded area in figure 14, both regulators preferred to restrict entry, because the relative weight on firm profits is larger than on external benefits. Since (x^{RO}, y^{RO}) maximizes regional welfare, both regulators restrict entry with permit limits and neither regulator has incentive to deviate toward a no permit strategy.

In all partitions other than (4), at least one regulator prefers to encourage entry. However, a quantity-based entry policy is only effective if the constraint on entry is binding. Since setting a permit level above the unregulated equilibrium level of entry will not attract entry, a permit regime is inconsequential when $x^{RO} + y^{RO} \geq n^U$. Furthermore, when $x^{RO} + y^{RO} \geq n^U$, the share of firms in either region is irrelevant because $\pi_i - F = 0$. Hence, the number of entrants is equal to the unregulated equilibrium level of entry (x^U, y^U) when $d > \min \{\underline{d}^A, \underline{d}^B\}$. □

²⁶Since I have treated the number of firms as a continuous variable thus far, I assume that the number of permits is also a continuous variable.

Figure 14: Parameter space in which permit equilibrium exists.



4.4 Welfare

This section compares the welfare outcomes of the price- and quantity-based entry policies from the two-region regulated equilibrium, described in propositions 4 and 5, with those of the social planner. Low Benefit represents the case where regulators prefer to discourage entry relative to the unregulated equilibrium (partition (4) in figure 12). Medium Benefit represents the case where the regionally optimal entry exceeds the unregulated equilibrium but neither regulator is willing to subsidize all entry (partitions (1) - (3) in figure 12). High Benefit represent the case where a single regulator subsidizes all entry despite the free riding rival regulator (partitions (5) - (9) in figure 12).

Tables 4, 5, and 6 contain the number of firms, aggregate welfare ($W^A + W^B$), equilibrium price ($P(Q)$), aggregate output (Q), total net profits ($\sum_i^n \pi_i - F$), and aggregate external benefit ($d\gamma Q$) for a series of simulations.²⁷

²⁷I continue using the same base set of parameters that I have used throughout the paper: $a = b = 1$, $c = 0$, $F = .2$, and $\gamma = 0.5$ unless otherwise specified. The share of consumption, $\gamma = 0.5$, is chosen for simplicity because the cutoffs in regions A and B coincide, $\underline{d}^A = \underline{d}^B = \underline{d} = 0.55$ and $\bar{d}^A = \bar{d}^B = \bar{d} = 1.65$. However, these comparisons hold for all (γ, d) -pairs with the defined partitions and can be provided by the authors upon request.

Table 4: Welfare comparisons of the unregulated equilibrium (n^U), single-region optimum ($n^R(\gamma = 0.5)$), two-region optimum (x^{RO}, y^{RO}), and social optimum ($n^R(\gamma = 1)$) when external benefits are low ($d = 0$).

	Unreg. Eq. ^p	Single-Region	Two-Region ^q	Social Optimal
Firms	1.23	0.54	0.95	0.71
Aggregate Welfare	0.15	0.18	0.18	0.19
Price	0.45	0.65	0.51	0.58
Aggregate Output	0.55	0.35	0.49	0.42
Aggregate Profit	0.00	0.12	0.06	0.10
External Benefit	0.00	0.00	0.00	0.00

^pdenotes the price-based entry policy two-region regulated equilibrium.

^qdenotes the quantity-based entry policy two-region regulated equilibrium.

The low benefit case, depicted in figure 4, assumes no external benefit, which coincides with the model in Mankiw and Whinston (1986). When regulators use an entry tax, the entry-stealing effect leads to the unregulated equilibrium, n^U . Since firms enter until net profits equal zero and the external benefit of consumption is zero, aggregate welfare consists of consumer surplus (0.15). When both regulators use permits, output is restricted to the regionally optimal number of firms (x^{RO}, y^{RO}) resulting in an aggregate welfare ($W^A + W^B$) of 0.18 which is greater than the 0.15 obtained from the unregulated equilibrium. The increase in welfare comes from the additional profits obtained by operating firms protected from competition by the permit restriction. However, the socially optimal outcomes require that the total number of permit issued in regions A and B be set even lower (0.71) than the regional optimum (0.95). By further restricting entry, aggregate welfare increases to (0.19) due to even higher aggregate firm profits (0.10).

Although not an equilibrium, the single-region level of entry (0.54) represents the preference of a single regulator when half of the output is exported. Since a smaller share of output is consumed domestically, the weight on firm profits is larger than in any other case, so the regulator restricts entry beyond the level of the social planner.

Table 5: Welfare comparisons of the unregulated equilibrium (n^U), single-region optimum ($n^R(\gamma = 0.5)$), two-region optimum (x^{RO}, y^{RO}), and social optimum ($n^R(\gamma = 1)$) when external benefits are medium ($d = 1$).

	Unreg. Eq. ^{pq}	Single-Region	Two-Region	Social Optimal
Firms	1.23	0.96	1.45	1.63
Aggregate Welfare	0.71	0.67	0.72	0.72
Price	0.45	0.51	0.41	0.38
Aggregate Output	0.55	0.49	0.59	0.62
Aggregate Profit	0.00	0.06	-0.05	-0.09
External Benefit	0.55	0.25	0.30	0.62

^pdenotes the price-based entry policy two-region regulated equilibrium.

^qdenotes the quantity-based entry policy two-region regulated equilibrium.

In the medium benefit case (figure 5), the unregulated equilibrium emerges because neither regulator chooses to augment the unregulated equilibrium with either a price or quantity entry policy. The unregulated equilibrium outcomes are equal to the low benefit case with the exception of external benefit, and subsequently aggregate welfare. The socially optimal entry (1.63) exceed the unregulated entry (1.23), but does not result in significant welfare gains. Since the social planner fully internalizes the positive pecuniary externality of production, it is willing to subsidize the entry despite the negative profits of each additional firm. In contrast, the single-region regulator would prefer to restrict entry since only half of consumer surplus and external benefits accrue domestically. Interestingly, the unregulated equilibrium results in a joint welfare larger than the single-region case. This result implies that for relatively low external benefits, the existence of a rival regulator entails a welfare improvement.

In the high benefit case (figure 6), the use of permits results in the unregulated equilibrium, and the use of subsidies results in the single-region regulated equilibrium n^R . The intuition for price equilibrium result is clear when comparing welfare a single regulator obtains by subsidizing entry (1.29) with the unregulated equilibrium (1.26). Net welfare increases by the difference in the external benefit gains (1.16-1.10=0.06) and profit loss (-0.3-0=-0.3)

Table 6: Welfare comparisons of the unregulated equilibrium (n^U), single-region optimum ($n^R(\gamma = 0.5)$), two-region optimum (x^{RO}, y^{RO}), and social optimum ($n^R(\gamma = 1)$) when external benefits are high ($d=2$).

	Unreg. Eq. ^q	Single-Region ^p	Two-Region	Social Optimal
Firms	1.23	1.38	1.89	2.39
Aggregate Welfare	1.26	1.29	1.37	1.39
Price	0.45	0.42	0.35	0.30
Aggregate Output	0.55	0.58	0.65	0.70
Aggregate Profit	0.00	-0.03	-0.15	-0.27
External Benefit	1.10	1.16	1.31	1.41

^pdenotes the price-based entry policy two-region regulated equilibrium.

^qdenotes the quantity-based entry policy two-region regulated equilibrium.

between the price equilibrium and the unregulated equilibrium. As a region moves toward autarky ($\gamma \rightarrow 1$, or conversely $\gamma \rightarrow 0$, the welfare outcomes of the price equilibrium converge to the socially optimal outcomes.

4.5 Conclusion

This model applies to governments that regulate a set of imperfectly competitive firms who choose to locate in one of two regions and produce identical goods with positive consumption externalities. Entry policies are used to influence market outcomes when political or legislative barriers impede the use of direct price and quantity policies. The existence of a rival regulator competing for firm location in a two-region economy creates pecuniary externalities that distort the incentives of a domestic regulator and influence optimal entry policy.

The preference for price- and quantity-based entry policies in the two-region case depends on the external benefit. When the external benefit is sufficiently low ($d \leq \min \{\underline{d}^A, \underline{d}^B\}$), a permit limit can induce the regionally optimal level of entry, whereas Bertrand-like competition drive entry taxes to zero. When the external benefit is high ($d > \min \{\underline{d}^A, \underline{d}^B\}$), positive pecuniary externalities create strong incentives to free ride off of the rival regulator's

entry subsidy. There exists a range of d ($\min \{\bar{d}^A, \bar{d}^B\} > d > \min \{\underline{d}^A, \underline{d}^B\}$) in which the incentive to free ride discourages either regulator from providing any entry subsidy resulting in the unregulated equilibrium. For sufficiently high external benefit ($d > \min \{\bar{d}^A, \bar{d}^B\}$), a domestic regulator provides an entry subsidy despite the free riding action of the rival regulator. Because subsidizing entry is costly, the welfare gains in the region with no production are greater than they would be if they subsidized entry as well.

These results have important implications about the use of entry policy in global markets. Regulators may have a strong incentive to free ride off of the policy in other regions when support for an industry is costly. Furthermore, the competition between regulators precludes the socially optimal number of entrants and suggests another role of international agreements. Regions may agree on an entry policy that coincides with that of the single-region planner who's jurisdiction spans both regions. However, it is important to note that both regulators would have the incentive to deviate from the agreement.

Chapter 5

Conclusion

This collection of essays illustrates the importance of understanding the incentives of economic agents when designing and analyzing natural resource and environmental policy. In chapter 2, I develop a model of wildfire response to show that residential structure damage is a top priority of wildfire management throughout the course of a fire. In chapter 3, I extend this model to account for the interaction between an individual fire manager and a regional command unit that allocates resources to potentially many fires. The model shows that a focus on structure damage may lead wildfire managers to shift response resources from suppression activity toward protection activity, which allows the wildfire to grow larger, burn longer, and ultimately cost more to suppress.

I empirically investigate the model predictions of wildfire duration, cost, size, and structure damage with several empirical specifications. In chapter 2, I develop a trivariate shared frailty hazard model that jointly estimates a set of cumulative outcomes and captures correlation between equations through a trivariate latent variable. I estimate wildfire duration, cost, and size with this joint hazard model and find that threatened homes and the potential for evacuation were significant indicators of wildfire duration, cost, and size. However, the model was reduced form and I could not distinguish between direct and indirect impacts of covariates on wildfire outcomes. In chapter 3, I estimate a dynamic panel model of theoretically consistent response resource allocation equations. This model provides information on the factors that influence resource allocation amongst several concurrent wildfire, and is used to generate instruments for committed resources in hazard regressions of wildfire cost and

size as well as a negative binomial regressions structure damage. The results provide further, and more direct, evidence that threatened residential structures influence fire manager behavior throughout the course of a response effort.

These results suggest that continued expansion of the WUI will further distort wildfire management incentives and lead to longer, larger, more destructive, and more expensive wildfires. Policies that force homeowners in the wildland urban interface to internalize the cost of their actions may slow the expansion of the WUI, and subsequently reduce future fire size and cost.

In chapter 4, I investigate the role of entry subsidies as an indirect policy instrument for promoting the consumption of goods with external benefits. I develop a two-region model in which regulators choose an entry policy to maximize domestic welfare. I use this model to show that there exists a range of parameters in which the socially optimal level of entry is precluded by a strong incentive to free ride off of a rivals policy. These results suggest an expanded role for international environmental agreements in coordinating entry policy across regions.

Appendix A

A.1 Comparative Dynamic Results

In this section, I derive the result $ds_f/d\nu_1 < 0$ and $ds_d/d\nu_1 > 0$ from the system of first order conditions of the recursive Bellman equation (2.6). Because I have data on threatened properties, which represent a subset of all threatened assets, I present this result in the context of an increase in $\nu_1 \in \boldsymbol{\nu}$. I begin by restating equation (2.6) and dropping the time notation for ease of exposition

$$V(f) = \min_{s_d, s_f \geq 0} \left\{ \ell[c(s_f, s_d), d(s_d)] + \int_0^\infty V' g(f' \mid f, s_f, \mathbf{x}) df' \right\}$$

where $c(\cdot)$ and $d(\cdot)$ are defined by (2.2) and (2.3), respectively. Assuming that $g(\cdot)$ is a continuous, but not necessarily stationary, distribution, the optimal feedback rules must satisfy the following first-order conditions,

$$\begin{aligned} \frac{\partial \ell[c(s_f, s_d), d(s_d)]}{\partial c} (w_f + w_f^o) + \int_0^\infty V' \frac{\partial g(f' \mid f, s_f, \mathbf{x})}{\partial s_f} df' &= 0 \\ \frac{\partial \ell[c(s_f, s_d), d(s_d)]}{\partial c} (w_d + w_d^o) - \frac{\partial \ell[c(s_f, s_d), d(s_d)]}{\partial d} \frac{y_1}{s_d^2} \nu_1 a(\mathbf{x}, f) &= 0 \end{aligned}$$

Then the FOCs can be totally differentiated and rearranged into the form $Ax = b$. For simplicity, I assume that the loss function is separable in costs and damages (i.e., $\partial^2 \ell / \partial c \partial d = 0$). This assumption is equivalent to equal weights on costs and damage in the loss function.

Alternative assumptions complicate the derivation but do not change the results.

$$\begin{aligned}
 & \begin{bmatrix} \frac{\partial^2 \ell}{\partial c^2} (w_f + w_f^o)^2 + \int_0^\infty V' \frac{\partial^2 g}{\partial s_f^2} & \frac{\partial^2 \ell}{\partial c^2} (w_d + w_d^o) (w_f + w_f^o) \\ \frac{\partial^2 \ell}{\partial c^2} (w_d + w_d^o) (w_f + w_f^o) & \frac{\partial^2 \ell}{\partial c^2} (w_d + w_d^o)^2 + \frac{\partial^2 \ell}{\partial d^2} \left(\frac{y_1 \nu_1 a}{s_d^2} \right)^2 + \frac{\partial \ell}{\partial d} \frac{y_1}{s_d^3} \nu_1 a \end{bmatrix} \begin{bmatrix} ds_a \\ ds_d \end{bmatrix} \\
 &= - \begin{bmatrix} 0 \\ -\frac{\partial^2 \ell}{\partial d^2} \frac{y_1}{s_d^3} (\nu_1 a)^2 - \frac{\partial \ell}{\partial d} \frac{1}{s_d^2} \nu_1 a \end{bmatrix} dy_1
 \end{aligned}$$

The equation can now be solved for ds_f/dy_1 and ds_d/dy_1 . I assume the following properties

- The loss function, $\ell[c(s_f, s_d), d(s_d)]$, is increasing in both arguments at an increasing rate
- The expectation of energy stock, $E_t\{\partial V'/\partial s_f\} = \int_0^\infty V' \frac{\partial g(f'|f, s_f, \mathbf{x})}{\partial s_f} df'$, conditional on suppression, is decreasing in suppression activity at a decreasing rate.

These properties are summarized in the following table.

$$\begin{array}{ccc}
 \frac{\partial \ell(c, d)}{\partial c} > 0 & \frac{\partial^2 \ell(c, d)}{\partial c^2} > 0 & i = c, d \\
 \frac{\partial g(f'|s_f)}{\partial s_f} < 0 & \frac{\partial g(f'|s_f)}{\partial s_f} \geq 0 &
 \end{array}$$

The determinant of A in the equation $Ax = b$ is positive definite, which implies

$$\begin{aligned}
 |A| &= \left(\overbrace{\frac{\partial^2 \ell}{\partial c^2} (w_f + w_f^o)^2}^+ + \overbrace{\int_0^\infty V' \frac{\partial^2 g}{\partial s_f^2} df'}^+ \right) \left(\overbrace{\left(\frac{\partial^2 \ell}{\partial c^2} (w_d + w_d^o)^2 \right)}^+ + \overbrace{\frac{\partial^2 \ell}{\partial d^2} \left(\frac{y_1 \nu a}{s_d} \right)^2}^+ + \overbrace{\frac{\partial \ell}{\partial d} \frac{y_1 \nu a}{s_d^3}}^+ \right) \\
 &\quad - \overbrace{\left(\frac{\partial^2 \ell}{\partial c^2} (w_d + w_d^o) (w_f + w_f^o) \right)^2}^+ > 0
 \end{aligned}$$

Then by Cramer's rule,

$$\frac{ds_f}{dy_1} = \frac{\left(-\frac{\partial^2 \ell}{\partial d^2} \frac{y_1}{s_d^3} (\nu_1 a)^2 - \frac{\partial \ell}{\partial d} \frac{y_1}{s_d^2} \nu_1 a\right) \frac{\partial^2 \ell}{\partial c^2} (w_d + w_d^o) (w_f + w_f^o)}{|A|} < 0$$

$$\frac{ds_d}{dy_1} = \frac{\left(\frac{\partial^2 \ell}{\partial c^2} (w_f + w_f^o)^2 + \int_0^\infty V' \frac{\partial^2 g}{\partial s_f^2}\right) \left(-\left(-\frac{\partial^2 \ell}{\partial d^2} \frac{y_1}{s_d^3} (\nu_1 a)^2 - \frac{\partial \ell}{\partial d} \frac{y_1}{s_d^2} \nu_1 a\right)\right)}{|A|} > 0$$

whereby each derivative is signed by the assumed properties of the comprising functions. I have shown that under fairly general assumptions, the sudden increase of threatened assets causes the wildfire management to increase protection while decreasing suppression effort. This result is due to the temporal effect of suppression. The moment an asset (e.g., home) becomes threatened, the management finds protection the most effective technique for reducing losses.

A.2 Tables

Interpretation of Hazard Model Parameter Estimates in Table 10

The coefficient estimates in a proportional hazard model represent a proportional shift of the baseline hazard function over the domain of the function (duration, cost, or area). The wildfire characterized by the baseline hazard function is described in Table 11. A negative sign on a covariate coefficient indicates that an increase in the associated variable leads to a downward shift in the hazard function. A downward shift in the hazard function implies a lower conditional probability of fire termination at any point in time (cost, or area). A lower probability of event occurrence leads to a longer expected fire duration (higher final costs, or larger final fire size). For example, an increase in the distance between a fire's point of ignition and the nearest town ($\ln(\text{Distance})$) leads to a reduction (-0.135) in the baseline area hazard function. This lower hazard function, representing the probability that the fire is contained, implies that the expected fire size is larger.

Table 7: Description of variables used throughout the paper.

Variable	Description
$s_d(t)$	protection effort at time t
$s_f(t)$	suppression effort at time t
$l(c(t), d(t), t)$	loss function
$a(t)$	instantaneous flow of area burning at time t
$A(t)$	cumulative burned area at time t
$c(t)$	instantaneous flow of management expenditure
$C(t)$	cumulative costs accrued until time t
$d(t)$	instantaneous flow of losses at time t
w_f	wage per unit of suppression fixed over duration of fire
$w_f^o(t)$	opportunity cost of suppression resources
w_d	wage per unit of protection fixed over duration of fire
$w_d^o(t)$	opportunity cost of protection resources
$\mathbf{y}(t)$	vector of asset densities
$\mathbf{z}(t)$	a vector of exogenous environmental and geographic characteristics at time t
$\boldsymbol{\nu}(t)$	a vector of threatened asset values at time t
$f(t)$	the fire's energy stock at time t measured in kilowatts
$g(f')$	probability density function of the fire stock in the next instant of time where $f' = \lim_{\Delta t \rightarrow 0} f(t + \Delta t)$
$G(f')$	cumulative distribution function (transition function) of the fire stock in the next instant of time
k	index of fire outcomes duration (t), cost (c), size (a)
$\phi_k(k \mathbf{x}(k))$	PDF describing the probability of the fire termination in the next unit of duration, cost, or size
$\Phi_k(k \mathbf{x}(k))$	CDF along dimension k
$\Psi_k(k \mathbf{x}(k))$	survival function along dimension k ($\Psi_k(k \mathbf{x}(k)) = 1 - \Phi_k(k \mathbf{x}(t))$)
$h_k(k \mathbf{x}(k))$	hazard function along dimension k ($= \phi_k / \Psi_k$)
$\phi(t, c, a \mathbf{x}(k))$	unconditional joint density
$\gamma(\mathbf{x}(k))$	exponential proportionality factor
ε_k	unobserved heterogeneity in equation k
$\boldsymbol{\varepsilon}$	jointly distributed unobserved heterogeneity
$\boldsymbol{\Omega}$	covariance matrix of unobserved heterogeneity $\boldsymbol{\varepsilon}$
$\boldsymbol{\beta}_k$	vector of covariate coefficients in equation k
δ	censoring indicator
ς_k	shape parameter in regression equation k
λ_k	scale parameter in regression equation k (subsumed into $\gamma(\cdot)$ for estimation)

Table 8: Variable labels used in this analysis, descriptions, and source information

Variable name	Brief description and source
Duration (t)	Duration is calculated as the difference measured in days between the report date:time (ICS box 1,2) and the discovery date:time (NIFMID) or start date:time (ICS box 7).
Cost (c)	Cost is the suppression cost to date (ICS box 19) in thousands of dollars.
Area (a)	Fire size is the total area burned to date (ICS box 15) in thousands of acres.
Threatened X_τ	Thousands of structures threatened lagged one period for $X=(\text{Residential}, \text{Commercial}, \text{Outbuildings})$ (ICS box 24).
Injuries $_\tau$	Number of reported injuries lagged one period (ICS box 22).
Fatalities $_\tau$	Number of reported fatalities lagged one period (ICS box 23).
Potential	Binary; equals 1 if evacuations were reported imminent (ICS box 25)
Evacuation $_\tau$	and 0 if no evacuation necessary. The variable is lagged one period.
Wind $_\tau$	Wind speed, mph/100 (ICS box 27).
Temperature $_\tau$	Temperature, degrees Fahrenheit/100 (ICS box 27).
Relative Humidity $_\tau$	Relative humidity on scale of 0 – 1 (ICS box 27).
Resource Scarcity $_\tau$	The sum of the growth of all other wildfires within a Forest Service region within five days of the report less the monthly average growth of fires in the region. Fire growth is calculated as the difference in acres burned between any two reports of a given fire ($a_t - a_{t-1}$); in 100 thousands of acres
Latitude	Latitude of fire start location, degrees/100 (ICS box 13).
Day of Year	Calculated by converting the report date into radians and applying sin and cos transformations.
Cause Lightning	Binary; equals 1 if cause of the wildfire is lightning (baseline=human) (ICS box 8).
Cause Unknown	Binary; equals 1 if cause is unknown or under investigation (baseline=human) (ICS box 8).
Year	Binary; equals 1 for fires that began in year $i = 2001, \dots, 2008$ (baseline is 2001)
FS Region i (name)	Binary; equals 1 for fires that began in Forest Service region $i = 1, \dots, 10$, respectively (baseline is region 8 (south))
Distance	The natural logarithm of the distance in miles between the ignition of a fire and the centroid of the nearest Census Designated Place (CDP); calculation based on the latitude and longitude from ICS box 13 and the 2010 Census.
Value20	The total housing value of any CDP with a centroid located 20 miles or less from the fire's point of ignition; in billions of dollars.

Table 9: Summary statistics of variables used in hazard model.

	Obs.	Mean	Std. Dev.	Min	Max
Duration	3,829	15.19	15.88	0.25	178.68
Cost	3,829	4,408.20	10,574.00	0.00	152,660.00
Area	3,829	23.81	77.17	0.00	1,322.90
Threatened Commercial	10,321	0.01	0.05	0.00	3.00
Threatened OutBuildings	10,321	0.04	0.24	0.00	5.00
Threatened Residential	10,321	0.11	0.57	0.00	24.00
Injuries	10,321	0.17	0.65	0.00	18.00
Fatalities	10,321	0.03	0.41	0.00	14.00
Potential Evacuation	10,321	0.31	0.46	0.00	1.00
Wind	10,321	0.07	0.06	0.00	0.90
Temperature	10,321	0.76	0.14	0.00	1.26
Relative Humidity	10,321	0.30	0.19	0.00	1.00
Resource Scarcity	10,321	0.00	1.22	-5.88	21.07
Latitude	3,829	0.41	0.07	0.25	0.67
Day of Year (Sin)	3,829	-0.20	0.52	-1.00	1.00
Day of Year (Cos)	3,829	-0.73	0.39	-1.00	1.00
Cause Lightning	3,829	0.65	0.48	0.00	1.00
Cause Unknown	3,829	0.16	0.37	0.00	1.00
Year	3,829	4.14	2.16	0.00	7.00
FS Region 6 (Pacific Northwest)	3,829	0.13	0.34	0.00	1.00
FS Region 5 (Pacific Southwest)	3,829	0.25	0.43	0.00	1.00
FS Region 1 (North)	3,829	0.18	0.38	0.00	1.00
FS Region 2 (Rocky Mountain)	3,829	0.04	0.20	0.00	1.00
FS Region 4 (Intermountain)	3,829	0.13	0.34	0.00	1.00
FS Region 9 (Eastern)	3,829	0.03	0.16	0.00	1.00
FS Region 3 (Southwest)	3,829	0.11	0.31	0.00	1.00
FS Region 10 (Alaska)	3,829	0.03	0.18	0.00	1.00
ln(Distance)	3,829	2.39	0.85	-1.75	4.33
Value20	3,829	3.31	17.83	0.00	283.98

Table 10: Parameter estimates of jointly estimated trivariate hazard model.

	Duration		Cost		Area	
	β_t	S.E.	β_c	S.E.	β_a	S.E.
Threatened Commercial	3.418***	(0.979)	1.743	(1.703)	-1.361	(3.966)
Threatened OutBuildings	-0.312	(0.541)	-1.542**	(0.761)	-3.003***	(0.997)
Threatened Residential	-0.822**	(0.319)	-2.007***	(0.385)	-2.312***	(0.460)
Injuries	0.098***	(0.038)	-0.137***	(0.051)	-0.034	(0.045)
Fatalities	-0.237***	(0.068)	-0.298***	(0.069)	-0.263***	(0.076)
Potential Evacuation	-0.792***	(0.079)	-1.460***	(0.071)	-1.613***	(0.087)
Wind	0.294	(0.290)	-0.115	(0.345)	-1.739***	(0.369)
Temperature	2.065***	(0.234)	0.837***	(0.161)	0.106	(0.334)
Relative Humidity	0.806***	(0.113)	1.151***	(0.121)	1.343***	(0.160)
Resource Scarcity	-0.255	(0.359)	-0.374*	(0.208)	-1.259***	(0.331)
Latitude	1.043	(0.904)	-2.187	(1.457)	-0.932*	(0.492)
Day of Year (Sin)	0.073*	(0.039)	0.138***	(0.048)	-0.018	(0.039)
Day of Year (Cos)	0.440***	(0.068)	0.481***	(0.058)	0.044	(0.064)
Cause Lightning	-0.740***	(0.055)	-0.206***	(0.057)	-0.496***	(0.053)
Cause Unknown	0.063	(0.055)	-0.025	(0.059)	0.034	(0.059)
Year	-0.042***	(0.010)	-0.028***	(0.009)	-0.024**	(0.010)
FS Region 6 (Pacific Northwest)	0.114	(0.138)	-0.741***	(0.153)	-0.155	(0.117)
FS Region 5 (Pacific Southwest)	0.691***	(0.089)	-0.824***	(0.090)	0.093	(0.092)
FS Region 1 (North)	-0.004	(0.139)	-0.431***	(0.155)	-0.113	(0.111)
FS Region 2 (Rocky Mountain)	0.522***	(0.134)	-0.449***	(0.123)	-0.058	(0.128)
FS Region 4 (Intermountain)	0.559***	(0.104)	-0.236**	(0.106)	-0.183*	(0.099)
FS Region 9 (Eastern)	0.449***	(0.118)	0.044	(0.148)	0.224**	(0.112)
FS Region 3 (Southwest)	0.400***	(0.090)	-0.461***	(0.094)	-0.317***	(0.097)
FS Region 10 (Alaska)	-0.024	(0.244)	-0.395	(0.528)	-1.238***	(0.241)
ln(Distance)	-0.100***	(0.026)	0.038	(0.024)	-0.135***	(0.025)
Value20	0.000	(0.001)	-0.001	(0.001)	0.001	(0.001)
Ancillary Parameters						
ς (shape)	1.263***	(0.017)	0.527***	(0.007)	0.624***	(0.008)
$\beta_0 = \varsigma_k \log(\lambda_k)$	-4.925***	(0.428)	-2.433***	(0.574)	0.378	(0.446)
Elements of the Cholesky Triangle						
Duration	0.825***	(0.038)	0		0	
Cost	0.790***	(0.048)	-0.063	(0.081)	0	
Area	0.931***	(0.049)	-0.082	(0.093)	0.009	(0.058)

Observations = 10,321; Number of Wildfires (n) = 3,829; Completed Fires = 3,398 $\ln L = -43,546$; Likelihood Ratio Statistic = 5,214 $\sim \chi^2_{84}$ * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

Table 11: Baseline and Median covariate values.

Continuous Covariates	Baseline	Median
Threatened Residential	0	0
Threatened Commercial	0	0
Threatened Outbuildings	0	0
Injuries	0	0
Fatalities	0	0
Wind (mph)	0	5
Temperature (°F)	0	79
Relative Humidity	0	0
Resource Scarcity	0	0
Latitude (0 = equator)	0	41°
Day of Year (Sin)	0	-.26
Day of Year (Cos)	0	-.89
Year	0 (2001)	5 (2006)
Distance	0	2.48
Value20	0	< 0.0001
Categorical Covariates		
Cause	Human	
Forest Service Region	8 (South)	

Appendix B

B.1 Data Definitions

Table 12: Variable labels used in this analysis, descriptions, and source information.

Variable name		Brief description and source
Cost		Cost is the suppression cost to date (ICS box 19) in dollars.
Area		Fire size is the total area burned to date (ICS box 15) in acres.
Damaged/Destroyed Residential Structures	Residential	Number of residential structures damaged and destroyed (ICS box 24).
Type 1 Crew		Number of type 1 crew firefighters (strike teams $\times$ 20) (ICS box 43)
Type 2 Crew		Number of type 2 crew firefighters (strike teams $\times$ 20) (ICS box 43)
Helicopter		Number of type 1, 2, and 3 helicopters (ICS box 43)
Dozer		Number of bulldozers and tractor plows (strike teams $\times$ 2) (ICS box 43)
Engine		Number of engines and water tenders (strike teams $\times$ 5) (ICS box 43)
Threatened Structures	Residential	Number (in hundreds) of residential structures threatened (ICS box 24).
WUI Interface		Acres of land (in thousands) with > 6 homes/km ² and $\leq 50\%$ vegetation within 2.4 km of land with $> 75\%$ vegetation (Radeloff et al., 2005).
WUI Intermix		Acres of land (in thousands) with > 6 homes/km ² and $> 50\%$ vegetation (Radeloff et al., 2005).
Log(Median Home Value)		County-level median home value in which the fire began (Census, 2012).
Potential Evacuation		Binary; equals 1 if there exist a potential for evacuation (ICS box 25) and 0 otherwise.
Injuries		Number of reported injuries (ICS box 21).
Windspeed		Average reported windspeed in mph over current operational period (ICS box 30).
Temperature		Average reported temperature in degrees Fahrenheit over current operational period (ICS box 30).

continued

<i>continued</i>	
Variable name	Brief description and source
Relative Humidity	Average reported relative humidity on scale of 0 – 100 over current operational period (ICS box 30).
Forecasted Windspeed	Forecasted windspeed in mph over next operational period (ICS box 34).
Forecasted Temperature	Forecasted temperature in degrees Fahrenheit over next operational period (ICS box 34).
Forecasted Relative Humidity	Forecasted relative humidity on scale of 0 – 100 over next operational period (ICS box 34).
Uncontrolled Perimeter	Approximation of wildfire perimeter not yet contained (in miles) (ICS).
Day of Year	Report date (ICS box 1) converted into radians and transformed with cosine function.
Human Caused	Binary; equals 1 if wildfire was caused by human activity (baseline=lightning) (ICS box 8).
County Roads	Miles of major collector road in county divided by county size (sq. miles) (USDOT, 2005).
Timber	Fuel Models = {H, R, E, P, U, G } (NIFMID).
Slope	Percent grade of slope at point of ignition (NIFMID).
Elevation	Elevation in thousands of feet at point of ignition (NIFMID).
Private Management	Binary; equals 1 if management agency=private (baseline=federal)
State Management	Binary; equals 1 if management agency=state (baseline=federal) (Census, 2012).

B.2 Dataset Merging Algorithm

The ICS-209 and NIFMID are datasets managed by two different organizations that do not use a common identifier. Therefore, I develop an algorithm to merge the two datasets based on variables common to both datasets. I use only the final observation from the ICS-209 dataset because the NIFMID data contain only one observation per fire representing the final ex-post report. The algorithm is outlined as follows:

1. Let $i = 1, \dots, n$ denote observations in the ICS-209 dataset and $j = 1, \dots, J$ denote observations from the NIFMID dataset. Calculate the following variables between an observation i and all fires $j = 1, \dots, J$: number of word matches, euclidean distance

(based on latitude and longitude), difference in start date, % difference in cost, and the % difference in size. These measures of deviation will be used to construct an index of best fit.

- Each dataset contains a variable for the wildfire name. The name variable in each dataset is broken up into individual words with each word in a separate variable (e.g., Bear Lake Fire would span name1=Bear, name2=Lake, and name3=Fire). The longest name contained six words so name1-name6 are created. Then for each i and j pair, 36 name match variables are created which take the value 1 if a name variable from the ICS-209 data match a name variable from the NIFMID data. These 36 variables are then summed and divided by the number of words in the wildfire for which a match is sought. This number is subtracted from 1 so that a perfect match gets a score of zero. In keeping with the Bear Lake Fire example, if a fire in the NIFMID data was named Bear Lake, two of the three words would match and the score would be $1 - \frac{2}{3} = \frac{1}{3}$.
- Distance is based on the latitude and longitude coordinates in each dataset. The pythagorean theorem is an approximation of the true distance because it does not take into account the curvature of the globe. I do not perceive this as a problem because of the relatively short distance between coordinates representing a match.
- The ICS-209 data reports an incident start date which is the approximate date of ignition. The NIFMID data reports a discovery date, ignition date, and first action date. The difference in days between ICS-209 start date and each of the three measure from the NIFMID is calculated and the minimum is used. The difference in days is divided by 10 to reduce the weight in the index of best fit.
- The percent difference in cost is the absolute value of the difference in the final suppression cost reported in the ICS-209 and NIFMID data divided by the

maximum of the cost figures reported in each dataset.

- The percent difference in the area is calculated analogously to the percent difference in cost
2. Potential matches are then screened for large deviations. NIFMID fires only qualify as a match if the ignition, discovery, or first action date is within 30 days of the ICS-209 start date. An additional qualification is that a potential NIFMID match must be in the same state and lie within approximately 60 miles of the ICS-209 fire.
 3. Each of the five components is summed to generate a weighted measure of fit for each i (ICS-209) and j (NIFMID) combination. The qualifying NIFMID observation with the minimum index of best fit is chosen as the most likely match.
 4. The matched data are then “scrubbed” for erroneous matches. The name match variable is recalculated after scrubbing the names for common words that often do not uniquely identify a fire. An online word counter (<http://www.wordcounter.com/>) recognizes the most commonly used words in the name variables (e.g., Fire, Creek, Road, etc.) and a simple loop deletes those entries if they are part of the fire name. The recalculated name match variable provides additional support for the quality of the match.

The Stata code is available on request.

B.3 Response Resource Conditions on Fires — i

I utilize the information in the ICS-209 dataset to locate and calculate a number of statistics representing conditions on other wildfires within the Geographic Area Coordination Center (GACC) region. Not all resources are necessarily allocated by the GACC, but during large fires or intervals with many fires, this assumption is not as strong. Since situation

reports will be filed almost daily during an active response effort, I search back 48 hours for fires burning within the region. I collect data on fires $-i$ for variables $j = \{\text{Type 1 Crew, Type 2 Crew, Helicopter, Dozer, Engine, Forecasted Temperature, Forecasted Wind-speed, Forecasted Humidity, Threatened Residential Structures, Potential Evacuation, and Uncontrolled Perimeter}\}$. The algorithm for collecting the data is outlined as follows:

- The data is sorted by the date and time of the submitted ICS-209 report.
- All wildfires that were documented with ICS-209 reports within a given region over the prior two days receive an indicator.
- ICS-209 reports may be filed multiple times in one day depending on the behavior and risks associated with a particular fire. In order to avoid counting resources multiple times, I take the maximum value of a variable, by fire, over the past 48 hours. The maximum value of the variable from each fire is then summed over all fires.

$$\sum_{i=1}^{n_t} \max_{ij}(x_{1ij}, x_{2ij}, x_{3ij}, \dots, x_{Z_{ij}}) \quad \forall j = 1, \dots, J$$

where $x_{z_{ij}}$ is the z_i observation of variable j associated with fire i , Z_i is the number of ICS-209 reports filed within 48 hours of the observation in question, and n_t is the number of fires burning at any time t .

- The forecasted weather variables are then divided by n_t to obtain an average rather than a sum.

The Stata code is available on request.

B.4 Summary Statistics

This section contains the summary statistics of the datasets used to estimate each model.

Table 13 contains the summary statistics of the covariates used to estimate the resource allocation equations. Tables 14, 15, 16 contained the summary statistics on the subset of data used to estimate the wildfire cost, size, and damage to structures equations.

Table 13: Summary statistics of covariates used in first-stage Arellano-Bond estimation.

	Obs.	Mean	Std. Dev.	Min	Max
Type 1 Crew	6,826	37.28	101.74	0	1,009
Type 1 Crew $-i$	6,826	9.19	85.60	0	1,504
Type 2 Crew	6,826	10.49	15.25	0	308
Type 2 Crew $-i$	6,826	7.67	49.89	0	634
Helicopter	6,826	5.28	4.63	0	96
Helicopter $-i$	6,826	1.18	7.38	0	112
Dozer	6,826	6.07	8.35	0	83
Dozer $-i$	6,826	2.86	19.03	0	233
Engine	6,826	32.22	32.78	0	262
Engine $-i$	6,826	52.92	183.18	0	1,258
Forecasted Temperature	6,355	79.85	12.37	0	116
Forecasted Temperature $-i$	6,427	80.32	12.02	0	116
Forecasted Windspeed	6,326	9.68	5.33	0	86
Forecasted Windspeed $-i$	6,406	9.95	5.10	0	76
Forecasted Humidity	6,344	25.49	14.16	0	100
Forecasted Humidity $-i$	6,421	26.08	13.98	0	100
Threatened Structures	6,178	197.39	448.93	0	4,300
Threatened Structures $-i$	6,826	0.81	17.22	0	1,026
Potential Evacuation	6,823	0.54	0.50	0	1
Potential Evacuation $-i$	6,826	5.51	5.65	0	24
Uncontrolled Perimeter	6,707	9.38	12.65	0	155
Uncontrolled Perimeter $-i$	6,826	24.60	55.06	0	468
Day of Year	6,826	-0.70	0.32	-1	1
Injuries ^a	5,577	0.32	0.88	0	13
Injuries ^a $-i$	6,826	0.46	1.93	0	21

^aOnly included as instruments in Arellano-Bond regressions.

Table 14: Summary statistics of covariates used in second-stage wildfire cost model.

	Obs.	Mean	Std. Dev.	Min	Max
Cost (\$)	249	8.5 M	15 M	85000	147 M
Type 1 Crew	1874	34.43	88.19	-6.21	786.55
Type 2 Crew	1874	9.44	9.40	-1.03	176.11
Helicopter	1874	5.20	3.16	0.51	29.21
Dozer	1874	5.52	6.33	-1.07	43.89
Engine	1874	31.23	25.51	-13.37	138.68
Thr. Residential	1874	174.00	439.42	0.00	4000.00
Log(Median Home Value)	1874	12.12	0.54	10.58	13.38
WUI Interface (ac)	1874	27.18	34.12	0.00	178.37
WUI Intermix (ac)	1874	60.64	69.51	0.00	323.20
Windspeed (mph)	1874	9.44	6.70	0.00	55.00
Temperature (F)	1874	76.98	12.32	29.00	113.00
Humidity	1874	26.33	16.26	2.00	100.00
Day of Year (Cos)	1874	-0.70	0.30	-1.00	0.75
Elevation (1000ft)	1874	5.18	2.35	0.16	10.16
Slope	1874	45.05	24.45	0.00	100.00
Timber	1874	0.61	0.49	0.00	1.00
Private Management	1874	0.00	0.07	0.00	1.00
State Management	1874	0.13	0.34	0.00	1.00

Table 15: Summary statistics of covariates used in second-stage wildfire size model.

	Obs.	Mean	Std. Dev.	Min	Max
Fire Size (ac)	216	21976.96	46979.67	83.00	499570.00
Type 1 Crew	1228	50.41	102.67	-3.69	684.73
Type 2 Crew	1228	10.33	10.79	-1.03	176.11
Helicopter	1228	5.71	3.59	0.51	29.21
Dozer	1228	6.64	7.21	-0.64	43.89
Engine	1228	35.40	27.52	-24.37	138.68
Thr. Residential	1228	266.24	588.62	0.00	4000.00
Log(Median Home Value)	1228	12.20	0.56	10.58	13.38
WUI Interface (ac)	1228	31.96	36.61	0.00	178.37
WUI Intermix (ac)	1228	73.46	76.88	0.00	323.20
Windspeed (mph)	1228	9.98	7.40	0.00	86.00
Temperature (F)	1228	78.51	12.63	9.00	113.00
Humidity	1228	24.52	15.26	3.00	100.00
Day of Year (Cos)	1228	-0.72	0.30	-1.00	0.47
Elevation (1000ft)	1228	4.82	2.35	0.16	9.85
Slope	1228	46.64	24.52	0.00	100.00
Timber	1228	0.60	0.49	0.00	1.00
Private Management	1228	0.00	0.05	0.00	1.00
State Management	1228	0.12	0.33	0.00	1.00

Table 16: Summary statistics of covariates used in second-stage wildfire structure damage model.

	Obs.	Mean	Std. Dev.	Min	Max
Dam./Des. Residential	746	0.23	2.92	0.00	58.00
Type 1 Crew	746	38.93	91.99	-6.21	509.75
Type 2 Crew	746	9.39	8.40	0.18	94.16
Helicopter	746	5.33	3.34	0.04	16.50
Dozer	746	5.47	6.19	-1.29	32.64
Engine	746	33.88	27.94	-13.37	132.79
Thr. Residential	689	302.14	587.33	0.00	3400.00
Log(Median Home Value)	746	12.23	0.55	10.94	13.29
WUI Interface (ac)	746	21.62	27.56	0.00	158.54
WUI Intermix (ac)	746	57.56	59.21	0.00	323.20
Windspeed (mph)	746	8.65	5.74	0.00	35.00
Temperature (F)	746	76.62	13.09	38.00	114.00
Humidity	746	27.94	16.99	2.00	100.00
Day of Year (Cos)	746	-0.70	0.30	-1.00	0.51
Elevation (1000ft)	746	4.83	2.04	1.30	10.16
Slope	746	48.37	26.72	0.00	100.00
Timber	746	0.69	0.46	0.00	1.00
Private Management	746	0.00	0.00	0.00	0.00
State Management	746	0.12	0.33	0.00	1.00
Human Caused	746	0.27	0.44	0.00	1.00
Country Roads	746	0.07	0.06	0.01	0.62

B.5 Long-Run Marginal Effects

Table 17: Long-run marginal effects of covariates on response resource allocation.

	Type 1 Crew		Type 2 Crew		Helicopter		Dozer		Engine	
	β	P-val	β	P-val	β	P-val	β	P-val	β	P-val
Resource $-i$	0.520	(0.288)	0.017	(0.041)	-0.006	(0.609)	0.015	(0.595)	0.001	(0.969)
Forecasted Temperature	0.064	(0.975)	-0.080	(0.050)	-0.014	(0.494)	-0.004	(0.952)	-0.052	(0.839)
Forecasted Temperature $-i$	1.845	(0.427)	0.092	(0.042)	0.021	(0.376)	0.117	(0.037)	0.532	(0.047)
Forecasted Windspeed	4.151	(0.270)	-0.066	(0.509)	0.025	(0.576)	0.009	(0.930)	-0.779	(0.342)
Forecasted Windspeed $-i$	-2.517	(0.407)	0.019	(0.843)	-0.021	(0.624)	0.043	(0.679)	1.608	(0.080)
Forecasted Humidity	-1.836	(0.286)	-0.084	(0.138)	-0.044	(0.051)	-0.102	(0.106)	-0.347	(0.240)
Forecasted Humidity $-i$	1.627	(0.403)	0.082	(0.162)	0.029	(0.261)	0.109	(0.047)	0.202	(0.462)
Thr. Residential	36.489	(0.179)	0.509	(0.121)	0.123	(0.376)	0.308	(0.515)	-0.204	(0.917)
Thr. Residential $-i$	-6.589	(0.879)	9.882	(0.403)	-0.043	(0.924)	3.393	(0.457)	-85.439	(0.523)
Potential Evacuation	55.902	(0.262)	2.151	(0.115)	2.001	(0.002)	3.574	(0.300)	-2.577	(0.823)
Potential Evacuation $-i$	-2.225	(0.621)	-0.239	(0.414)	-0.137	(0.090)	-0.045	(0.942)	2.009	(0.069)
Uncontrolled Perimeter	2.966	(0.224)	0.144	(0.036)	0.159	(0.002)	0.566	(0.152)	1.208	(0.085)
Uncontrolled Perimeter $-i$	-0.189	(0.455)	-0.003	(0.505)	-0.002	(0.493)	-0.016	(0.180)	-0.042	(0.582)
Day of Year	38.751	(0.379)	-6.270	(0.000)	0.219	(0.769)	0.926	(0.820)	-4.514	(0.611)

* P-values calculated by the delta method

B.6 Response Resource Allocation Equations

All response resource equations utilize 6,826 observations on 642 wildfires. Each equation contains a lagged dependent variable and the same set of explanatory covariates, some of which are endogenous. The endogenous covariates (including the lagged dependent variable) are instrumented in each model by a set of lags of covariates, both exogenous and endogenous. All weather covariates are considered strictly exogenous and instrument themselves and the endogenous covariates. The choice of instruments in the difference equation is allowed to differ from the instruments chosen for the level equation. This section of the appendix details the construction of the instrument matrix based on Arellano-Bond first-difference autocorrelation tests (from now on AB test) and Hansen test of overidentification. Table 18 contains p-values of the AB test for 15 lags.

An AR(1) process is always expected because the dependent variable $\Delta y_t = y_t - y_{t-1}$ and the lagged dependent variable $\Delta y_{t-1} = y_{t-1} - y_{t-2}$ both contain y_{t-1} in the first difference equation. Therefore, results from the AB test indicate that first-order autocorrelation does in fact exist. As detailed in Arellano and Bond (1991), a test of autocorrelation in the levels equation is not informative because the fixed component of the error structure is shared by all observations within a panel.

With large unbalanced panels, instruments from lags are abundant. However, overidentification becomes problematic when all possible lags are used as instruments. I collapse the instrument matrix, as described in Roodman (2006), and restrict the number of lags because the largest panel contains 143 observations (the mean is 10.4 observations).

Type 1 Crew.

Difference equation instruments from lags: 2, 5-6, 9-10, and 13-15

Level equation instruments from lags: 3-6

Total instruments: 128

Table 18: P-values of Arellano-Bond test of first-difference autocorrelation.

AB Test	Crew1	Crew2	Helicopter	Tractor	Engine
AR(1)	0.0001	0.0201	0.0723	0.0001	0.0001
AR(2)	0.9090	0.7873	0.3907	0.0556	0.1820
AR(3)	0.5548	0.8779	0.4632	0.9664	0.2753
AR(4)	0.7832	0.1295	0.1035	0.2152	0.3891
AR(5)	0.5740	0.3341	0.1233	0.9417	0.6958
AR(6)	0.2006	0.1938	0.6596	0.7328	0.6297
AR(7)	0.2011	0.1834	0.9305	0.3975	0.2490
AR(8)	0.2781	0.6778	0.5658	0.4624	0.5472
AR(9)	0.3609	0.6046	0.9550	0.8754	0.9463
AR(10)	0.3272	0.3322	0.1600	0.8864	0.7813
AR(11)	0.1007	0.1260	0.3086	0.5689	0.3373
AR(12)	0.1227	0.5050	0.5589	0.4677	0.8707
AR(13)	0.6448	0.1442	0.7823	0.7324	0.1768
AR(14)	0.6805	0.7035	0.8946	0.7178	0.1292
AR(15)	0.9033	0.4772	0.8826	0.3167	0.0581

H_0 = autocorrelation does not exist in the first difference errors

In addition to lags of the estimated covariates, injuries on fire i , and injuries that occur on all other fires $-i$ at time t are included as external instruments to capture the reaction of fire managers to firefighter injury. I do not include these additional covariates in the Helicopter, Dozer, or Engine models because I do not expect that these covariates would impact the allocation of capital resources.

Type 2 Crew.

Difference equation instruments from lags: 2-3, 8-10, and 14

Level equation instruments from lags: 2-3, and 14

Total instruments: 98

Helicopter.

Difference equation instruments from lags: 2-3, 6-9, and 12-15

Level equation instruments from lags: 6

Total instruments: 96

Dozer.

Difference equation instruments from lags: 2-3, 6-9, and 12-15

Level equation instruments from lags:

Total instruments: 32

Engine.

Difference equation instruments from lags: 9-10

Level equation instruments from lags: 5-7, and 11

Total instruments: 56

B.7 Arellano-Bond Specification Test

Roodman (2006) and Bond (2002) suggest that the researcher may check the estimates of the Arellano-Bond systems estimator by comparing the estimate of the lagged dependent variable to the estimates of the lagged dependent variable in a fixed effects and pooled OLS regression. An estimate near the pooled OLS estimate (upper bound) implies that unmodeled shocks may be inflating the lagged dependent variable estimate by attributing some fixed effect to the lagged dependent variable. An estimate near the fixed-effect estimate (lower bound) implies that the dynamic panel bias caused by the transformation of the within-group estimator (and subsequent negative correlation between y_{t-1} and $-\frac{1}{T-1}v_{t-1}$) deflates the estimate of the lagged dependent variable. I present the 95% confidence intervals of the lagged dependent variable estimates for the fixed effect, Arellano-Bond, and pooled OLS models.

The lagged dependent variable estimate in the Type 1 Crew model is not statistically different from that in the pooled OLS model (upper bound). This result implies that important omitted covariates may be causing the model to attribute fixed effects to the lagged dependent variable. The lagged dependent variable estimates in the Type 2 Crew, Helicopter, Dozer, and Engine models all lie well within the reasonable range.

Table 19: Upper (pooled OLS) and lower (fixed effects) bounds on lagged dependent variable in Arellano-Bond models.

Equation	Fixed-Effect	Arellano-Bond	Pooled OLS
Type 1 Crew	[0.740, 0.769]	[0.928, 1.005]	[0.948, 0.964]
Type 2 Crew	[0.528, 0.567]	[0.384, 0.715]	[0.695, 0.727]
Helicopter	[0.627, 0.664]	[0.531, 0.852]	[0.844, 0.869]
Dozer	[0.746, 0.775]	[0.578, 0.954]	[0.931, 0.949]
Engine	[0.781, 0.806]	[0.867, 0.942]	[0.936, 0.952]

Appendix C

C.1 Proof of Lemma 1

The equilibrium profit function of each firm is decreasing in the number of entrants. In particular,

$$\frac{\partial \pi_i(n)}{\partial n} = -\frac{2(a-c)^2}{b(n+1)^3}$$

where $a > c$ by assumption. Since, in addition it is profitable for at least one firm to enter (i.e., $F < F_{max} \equiv \frac{(a-c)^2}{b^4}$), the equilibrium is guaranteed to exist and be unique.

C.2 Proof of Lemma 2

The number of entrants n^R maximizes $W(n)$ if it solves $W'(n) = 0$ and $W''(n) < 0$. The second derivative of the welfare function is

$$W''(n) = -\frac{(a-c)^2(2n-1)\gamma}{b(n+1)^4} + \frac{6n(a-c)^2}{b(n+1)^4} - \frac{4(a-c)^2}{b(n+1)^3} - \frac{2(a-c)d\gamma}{b(n+1)^3}$$

where the first and last terms are consumer surplus and the external benefit and are both concave in $n > 1$. The middle terms come from producer surplus and are only concave when $n < 2$. The sum of multiple concave functions is itself concave. If $n > 2$, the concavity of consumer surplus and external benefits must outweigh the convexity of producer surplus.

This occurs when

$$\gamma < \frac{2(a-c)(n-2)}{2d(1+n) + (a-c)(2n-1)}.$$

These conditions are satisfied for all parameters used to generate figures and simulations.

C.3 Proof of Lemma 3

Suppose that $n^R > n^U$ when $\gamma CS_n(n^U) + D_n(n^U) < n\pi_n(n^U)$. Then it must be the case that at n^U , a marginal increase in the number of entrants yields more welfare. However, we know that the social marginal cost of entry is $n\pi_n(n^U)$, and the social marginal benefit of entry is $\gamma CS_n(n^U) + \pi_i(n^U) - F + D_n(n^U)$. By definition, $\pi_i(n^U) - F = 0$, which implies that the social marginal benefit of entry at the unregulated equilibrium is $\gamma CS_n(n^U) + D_n(n^U)$. If a marginal increase in the number of entrant was welfare improving, the social marginal benefit of entry would exceed the social marginal cost: $\gamma CS_n(n^U) + D_n(n^U) > n\pi_n(n^U)$. This contradicts the original statement. Therefore $\gamma CS_n(n^U) + D_n(n^U) < n\pi_n(n^U)$.

The result of lemma 3 may be expressed as a threshold in terms of the external benefit, d . Rearranging the first-order conditions of the regulator's welfare maximization problem we obtain and isolating the parameter d ,

$$n^U \gamma \frac{(a-c)^2}{b(1+n^U)^3} + d\gamma \frac{a-c}{b(n^U+1)^2} = 2n^U \frac{(a-c)^2}{b(1+n^U)^3}$$

and solving for the parameter d , we have

$$d = \left(\frac{(2-\gamma)(a-c)}{\gamma} \right) \left(\frac{n^U}{n^U+1} \right)$$

which, evaluated at $n^u = \frac{a-c}{\sqrt{Fb}} - 1$ yields

$$\bar{d} \equiv \left(\frac{2}{\gamma} - 1 \right) \left(a - c - \sqrt{Fb} \right).$$

C.4 Proof of Lemma 6

Proof of lemma 6 follows the same logic as the single-region counterpart in lemma 3. Since any (x, y) -pair that satisfies $x + y = n^U$ is a single-region unregulated equilibrium as specified in lemma 4, assume that $x^U = y^U = \frac{1}{2}n^U$ and n^U denotes the aggregate number of entrants when convenient. Suppose that $(x^{RO}, y^{RO}) \gg (x^U, y^U)$ when both

$$W_x^A(n^U) \equiv \gamma C S_x(n^U) + \pi_i^A(n^U) - F + D_x^A(n^U) - x \pi_{ix}^A(n^U) < 0$$

$$W_y^B(n^U) \equiv (1 - \gamma) C S_y(n^U) + \pi_i^B(n^U) - F + D_y^B(n^U) - y \pi_{iy}^B(n^U) < 0$$

where $\pi_i^k(n^U) - F = 0$ by definition. If regulator A could increase welfare by inducing $x^{RO} > x^U$, marginal welfare at x^U would be positive, which contradicts the original statement. An analogous argument holds for regulator B . Therefore $(x^{RO}, y^{RO}) \gg (x^U, y^U)$ if and only if $W_x^A(n^U) > 0$ and $W_y^B(n^U) > 0$.

These inequalities can then be used to derive a cutoff in terms of the external benefit, d . The regionally optimal and privately optimal level of entry coincide in region A when

$$\gamma \frac{n^U (a - c)^2}{b(1 + n^U)^3} + d^A \gamma \frac{a - c}{b(b(1 + n^U)^2)} = \frac{n^U (a - c)^2}{b(1 + n^U)^3}$$

and solving for d^A , we have

$$\underline{d}^A \equiv \left[\frac{n^U}{1 + n^U} \frac{a - c}{b} \right] \frac{1 - \gamma}{\gamma}$$

which, evaluated at $n^u = \frac{a-c}{\sqrt{Fb}} - 1$ is

$$\underline{d}^A \equiv \frac{b(1 - \gamma)}{\gamma} \left(a - c - \sqrt{Fb} \right).$$

Since the region B welfare function is distinguished from region A by the inverse share of domestic consumption $(1 - \gamma)$, the cutoff in region B is obtained by substituting $(1 - \gamma)$ for

γ in $\underline{d}^A$.

$$\underline{d}^B \equiv \frac{b\gamma}{1-\gamma} \left(a - c - \sqrt{Fb} \right)$$

Bibliography

- Abt, Karen L., Jeffrey P. Prestemon, and Krista Gebert (2008). “Forecasting wildfire suppression expenditures for the United States Forest Service”. In: *The Economics of Forest Disturbances*. Ed. by Karen Abt, Jeffrey P. Prestemon, and Thomas P. Holmes. Springer. Chap. 17.
- Abt, K.L., J.P. Prestemon, and K.M. Gebert (2009). “Wildfire Suppression Cost Forecasts for the US Forest Service”. *Journal of Forestry*, 107(4): pp. 173–178.
- Altay, N. and W.G. Green (2006). “OR/MS Research in Disaster Operations Management”. *European Journal of Operational Research*, 175(1): pp. 475–493.
- Andersen, Per Kragh et al. (1997). “Estimation of Variance in Cox’s Regression Model with Shared Gamma Frailties”. *Biometrics*, 53(4): pp. 1475–1484.
- Arellano, Manuel and Stephen Bond (1991). “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations”. *The Review of Economic Studies*, 58(2): pp. 277–297.
- Arellano, Manuel and Olympia Bover (1995). “Another Look at the Instrumental Variable Estimation of Error-Components Models”. *Journal of Econometrics*, 68(1): pp. 29–51.
- Barrett, Scott (1994). “Strategic Environmental Policy and International Trade”. *Journal of Public Economics*, 54(3): pp. 325–338.
- Bassey, K.J. and P.E. Chigbu (2012). “On Optimal Control Theory in Marine Oil Spill Management: A Markovian Decision Approach”. *European Journal of Operational Research*, 217(2): pp. 470–478.
- Baumol, William J and Wallace E Oates (1988). *The Theory of Environmental Policy*. Cambridge University Press.

- Bayaliyev, Alim, Julia Kalloz, and Matt Robinson (2011). "Chinas Solar Policy: Subsidies, Manufacturing Overcapacity & Opportunities". Accessed on June 20, 2012 at http://solar.gwu.edu/Research/ChinaSolarPolicy_BayaKallozRobins.pdf.
- Bayındır-Upmann, Thorsten (2003). "Strategic Environmental Policy Under Free Entry of Firms". *Review of International Economics*, 11(2): pp. 379–396.
- Bennett, Neil G., Ann Klimas Blanc, and David E. Bloom (1988). "Commitment and the Modern Union: Assessing the Link Between Premarital Cohabitation and Subsequent Marital Stability". *American Sociological Review*, 53(1): pp. 127–138.
- Bhattacharjea, Aditya (2002). "Foreign Entry and Domestic Welfare: Lessons for Developing Countries". *Journal of International Trade & Economic Development*, 11(2): pp. 143–162.
- Blossfeld, Hans-Peter, Alfred Hamerle, and Karl Ulrich Mayer (1989). *Event History Analysis: Statistical Theory and Application in the Social Sciences*. L. Erlbaum Associates.
- Blundell, Richard and Stephen Bond (1998). "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models". *Journal of Econometrics*, 87(1): pp. 115–143.
- Bond, Stephen R (2002). "Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice". *Portuguese Economic Journal*, 1(2): pp. 141–162.
- Brander, James A. and Barbara J. Spencer (1981). "Tariffs and the Extraction of Foreign Monopoly Rents Under Potential Entry". *Canadian Journal of Economics*, pp. 371–389.
- (1985). "Export Subsidies and International Market Share Rivalry". *Journal of international Economics*, 18(1): pp. 83–100.
- Bratten, Frederick W (1970). *Allocation Model for Firefighting Resources – A Progress Report*. Vol. 214. Forest Service, US Dept. of Agriculture, Pacific Southwest Forest and Range Experiment Station.
- Butry, David and Geoffrey Donovan (2008). "Protect Thy Neighbor: Investigating the Spatial Externalities of Community Wildfire Hazard Mitigation". *Forest Science*, 54(4): pp. 417–428.

- Butry, David, Marcia Gumpertz, and Marc Genton (2008). “The Production of Large and Small Wildfires”. In: *The Economics of Forest Disturbances*. Ed. by Karen Abt, Jeffrey P. Prestemon, and Thomas P. Holmes. Springer. Chap. 5.
- Butry, D.T. (2009). “Fighting Fire with Fire: Estimating the Efficacy of Wildfire Mitigation Programs Using Propensity Scores”. *Environmental and Ecological Statistics*, 16(2): pp. 291–319.
- CABOE (2013). *California State Board of Equalization: Fire Prevention Fee*. URL: http://www.boe.ca.gov/sptaxprog/fire_prev_fee.htm.
- Calkin, David et al. (2005). *Comparing Resource Values at Risk from Wildfires with Forest Service Fire Suppression Expenditures: Examples from 2003 Western Montana Wildfire Season*. Research Note RMRS-RN-24WWW. United States Department of Agriculture, Forest Service, Rocky Mountain Research Station.
- Calkin, David E et al. (2013). “Estimating US Federal Wildland Fire Managers Preferences Toward Competing Strategic Suppression Objectives”. *International Journal of Wildland Fire*, 22(2): pp. 212–222.
- Cameron, A.C. and P.K. Trivedi (2005). *Microeconometrics: Methods and Applications*. Cambridge University Press.
- Cardille, Jeffrey, Stephen Ventura, and Monica Turner (2001). “Environmental and social factors influencing wildfires in the upper Midwest, United States”. *Ecological Applications*, 11(1): pp. 111–127.
- Cato, Susumu (2010). “Emission Taxes and Optimal Refunding Schemes with Endogenous Market Structure”. *Environmental and Resource Economics*, 46(3): pp. 275–280.
- Census (2012). “American FactFinder”. U.S. Census. Housing: Financial Characteristics: Median Home Value (years 2001-2010).

- Covington, W Wallace and Margaret M Moore (1994). "Southwestern Ponderosa Forest Structure: Changes Since Euro-American Settlement". *Journal of Forestry*, 92(1): pp. 39–47.
- Cox, DR (1972). "Regression Models and Life-Tables". *Journal of the Royal Statistical Society. Series B (Methodological)*, 34(2): pp. 187–220.
- DeRemer, David R. (2011). "The Evolution of International Subsidy Rules". Columbia University Working Paper. Accessed on February 4, 2013.
- Dietz, Simon, Eric Neumayer, and Indra De Soysa (2007). "Corruption, the Resource Curse and Genuine Saving". *Environment and Development Economics*, 12(1): pp. 33–53.
- Donovan, Geoffrey H. and Thomas C. Brown (2005). "An Alternative Incentive Structure for Wildfire Management on National Forest Land". *Forest Science*, 51(5): pp. 387–395.
- Donovan, Geoffrey H. and Douglas B. Rideout (2003). "An Integer Programming Model to Optimize Resource Allocation for Wildfire Containment". *Forest Science*, 49(2): pp. 331–335.
- Donovan, G.H., P. Noordijk, and V. Radeloff (2004). "Estimating the Impact of Proximity of Houses on Wildfire Suppression Costs in Oregon and Washington". In: *2nd Symposium on Fire Economics and Policy: A Global View*, pp. 19–22.
- Eaton, Jonathan and Gene M. Grossman (1986). "Optimal Trade and Industrial Policy under Oligopoly". *The Quarterly Journal of Economics*, 101(2): pp. 383–406.
- Embrechts, P., C. Klüppelberg, and T. Mikosch (1997). *Modelling Extremal Events for Insurance and Finance*. Vol. 33. Springer Verlag.
- Espinola-Arredondo, Ana and Felix Munoz-Garcia (2011). "Free-Riding in International Environmental Agreements: A Signaling Approach to Non-Enforceable Treaties". *Journal of Theoretical Politics*, 23(1): pp. 111–134.
- Etro, Frederico (2011). "Endogenous Market Structures and Strategic Trade Policies". *International Economic Review*, 52(1): pp. 63–84.

- Etzioni, R.D. et al. (1999). “On the use of survival analysis techniques to estimate medical care costs”. *Journal of Health Economics*, 18(3): pp. 367–382.
- FAMWEB (2012). “National Fire and Aviation Management Web Applications: SIT Reports”. Accessed in July, 2012 at <https://fam.nwcg.gov/fam-web/>.
- Fenichel, Eli P. et al. (2011). “Adaptive human behavior in epidemiological models”. *Proceedings of the National Academy of Sciences*, 108(15): pp. 6306–6311.
- Finney, Mark, Isaac C. Grenfell, and Charles W. McHugh (2009). “Modeling Containment of Large Wildfires Using Generalized Linear Mixed-Model Analysis”. *Forest Science*, 55(3): pp. 249–255.
- Finney, Mark A. (1998). *FARSITE: Fire Area Simulator Model Development and Evaluation*. Research Paper RMRS-RP-4. United States Department of Agriculture, Forest Service, Rocky Mountain Research Station.
- Finnoff, David et al. (2005). “The Importance of Bioeconomic Feedback in Invasive Species Management”. *Ecological Economics*, 52(3): pp. 367–381.
- FIREScope (2012). “ICS RESOURCES LISTING”. Accessed in March, 2013 at <http://www.firescope.org>.
- Fraser, Christophe et al. (2004). “Factors that make an infectious disease outbreak controllable”. *Proceedings of the National Academy of Sciences*, 101(16): pp. 6146–6151.
- Fried, Jeremy S, Margaret S Torn, and Evan Mills (2004). “The Impact of Climate Change on Wildfire Severity: A Regional Forecast for Northern California”. *Climatic Change*, 64(1-2): pp. 169–191.
- Fried, J.S., J.K. Gillespie, and J. Spero (2006). “Analysing Initial Attack on Wildland Fires using Stochastic Simulation”. *International Journal of Wildland Fire*, 15(1): pp. 137–146.
- Fujiwara, Kenji (2009). “Environmental Policies in a Differentiated Oligopoly Revisited”. *Resource and Energy Economics*, 31(3): pp. 239–247.

- Gebert, Krista, David Calkin, and Jonathan Yoder (2007). “Estimating suppression expenditures for individual large wildland fires”. *Western Journal of Applied Forestry*, 22(3): pp. 188–196.
- Gebert, Krista M. et al. (2008). “Economic Analysis of federal wildfire management programs”. In: *The Economics of Forest Disturbances*. Ed. by Jeffrey P. Prestemon Thomas P. Holmes and Karen L. Abt. Forestry Sciences. Springer. Chap. 15, pp. 295–322.
- Golombek, Rolf and Michael Hoel (2011). “International Cooperation on Climate-Friendly Technologies”. *Environmental and Resource Economics*, 49(4): pp. 473–490.
- Greaker, Mads (2003). “Strategic Environmental Policy; Eco-dumping or a Green Strategy?” *Journal of Environmental Economics and Management*, 45(3): pp. 692–707.
- Greene, William (2008). *Econometric Analysis*. Sixth Edition. Pearson Prentice Hall.
- Gude, Patricia H et al. (2013). “Evidence for the Effect of Homes on Wildfire Suppression Costs”. *International Journal of Wildland Fire*.
- Haight, R.G. and Jeremy S. Fried (2007). “Deploying Wildland Fire Suppression Resources with a Scenario-Based Standard Response Model”. *INFOR: Information Systems and Operational Research*, 45(1): pp. 31–39.
- Haufler, Andreas and Ian Wooton (2010). “Competition for Firms in an Oligopolistic Industry: The Impact of Economic Integration”. *Journal of International Economics*, 80(2): pp. 239–248.
- Hirsch, KG and DL Martell (1996). “A Review of Initial Attack Fire Crew Productivity and Effectiveness”. *International Journal of Wildland Fire*, 6(4): pp. 199–215.
- Holmes, Thomas, Robert Jr. Huggett, and Anthony Westerling (2008). “Statistical Analysis of Large Wildfires”. In: *The Economics of Forest Disturbances*. Ed. by Karen Abt, Jeffrey P. Prestemon, and Thomas P. Holmes. Springer. Chap. 4.
- IEA (2011). *Trends in Photovoltaic Applications: Survey report of selected IEA countries between 1992 and 2010*. Tech. rep. IEA-PVPS T1-20:2011. International Energy Agency.

- Jain, A.K. and R.L. Strawderman (2002). "Flexible Hazard Regression Modeling for Medical Cost Data". *Biostatistics*, 3(1): pp. 101–118.
- Janeba, Ekhard (1998). "Tax Competition in Imperfectly Competitive Markets". *Journal of International Economics*, 44(1): pp. 135–153.
- Kalbfleisch, John D. and Ross L. Prentice (1980). *The Statistical Analysis of Failure Time Data*. Vol. 5. Wiley New York.
- Katsoulacos, Yannis and Anastasios Xepapadeas (1995). "Environmental Policy under Oligopoly with Endogenous Market Structure". *The Scandinavian Journal of Economics*, pp. 411–420.
- KCFAST (2012). "National Interagency Fire Management Integrated Database Wildfire Data". Accessed in July, 2012 at <https://fam.nwcg.gov/fam-web/kcfast/mnmenu.htm>.
- Kennedy, Peter W. (1994). "Equilibrium Pollution Taxes in Open Economies with Imperfect Competition". *Journal of environmental economics and management*, 27(1): pp. 49–63.
- King, G. (1989). "A Seemingly Unrelated Poisson Regression Model". *Sociological Methods & Research*, 17(3): pp. 235–255.
- Kirsch, A.G. and D.B. Rideout (2005). "Optimizing Initial Attack Effectiveness by Using Performance Measures". In: *Systems Analysis in Forest Resources: Proceedings of the 2003 Symposium, October 7-9, 2003, Stevenson, Washington*. Vol. 656, pp. 183–187.
- Liang, J. et al. (2008). "Factors Influencing Large Wildland Fire Suppression Expenditures". *International Journal of Wildland Fire*, 17(5): pp. 650–659.
- Liu, L., R.A. Wolfe, and J.D. Kalbfleisch (2006). "A Shared Random Effects Model for Censored Medical Costs and Mortality". *Statistics in Medicine*, 26(1): pp. 139–155.
- Ludkovski, Michael and Jarad Niemi (2010). "Optimal Dynamic Policies for Influenza Management". *Statistical Communications in Infectious Disease*, 2(1): pp. 1–25.
- Mankiw, N. Gregory and Michael D. Whinston (1986). "Free Entry and Social Inefficiency". *The RAND Journal of Economics*, 17(1): pp. 48–58.

- Markusen, James R., Edward R. Morey, and Nancy Olewiler (1995). "Competition in Regional Environmental Policies when Plant Locations are Endogenous". *Journal of Public Economics*, 56(1): pp. 55–77.
- Mathworks (2010). *Matlab*. V 7.10.0.499 (R2010a).
- Mees, R. and D. Strauss (1992). "Allocating Resources to Large Wildland Fires: A Model with Stochastic Production Rates". *Forest science*, 38(4): pp. 842–853.
- Mercer, D. Evan and Jeffrey P. Prestemon (2005). "Comparing Production Function Models for Wildfire Risk Analysis in the Wildland-Urban Interface". *Forest Policy and Economics*, 7(5): pp. 782–795.
- Meyer, Bruce D. (1990). "Unemployment Insurance and Unemployment Spells". *Econometrica*, 58(4): pp. 757–782.
- Mintz, Jack and Henry Tulkens (1986). "Commodity Tax Competition Between Member States of a Federation: Equilibrium and Efficiency". *Journal of Public Economics*, 29(2): pp. 133–172.
- NICC (2012). "ICS-209: When to Report Wildland Fire Incidents". National Interagency Coordination Center Predictive Services. Accessed in April, 2013 at <http://www.predictiveservices.nifc.gov/>.
- NIFC (2011). "National Call When Needed Helicopter Service Contract". National Interagency Fire Center. Accessed in March, 2013 at http://www.fs.fed.us/fire/contracting/helicopters_cwn/helicopter_contract_cwn.pdf.
- Petersen, Trond. (1995). "Analysis of Event Histories". In: *Handbook of Statistical Modeling for the Social and Behavioral Sciences*. Ed. by Gerhard Arminger, Clifford C. Clogg, and Michael E. Sobel. Plenum Publishing Corporation, pp. 453–517.
- Petrovic, N., D.L. Alderson, and J.M. Carlson (2012). "Dynamic Resource Allocation in Disaster Response: Tradeoffs in Wildfire Suppression". *PloS one*, 7(4): e33285.

- Petrovic, N. and JM Carlson (2012). “A Decision-Making Framework for Wildfire Suppression”. *International Journal of Wildland Fire*.
- Pflüger, Michael and Jens Südekum (2013). “Subsidizing Firm Entry in Open Economies”. *Journal of Public Economics*, 97(0): pp. 258–271.
- Pich, M.T., C.H. Loch, and A. De Meyer (2002). “On Uncertainty, Ambiguity, and Complexity in Project Management”. *Management Science*, 48(8): pp. 1008–1023.
- Plucinski, MP et al. (2012). “The Effect of Aerial Suppression on the Containment Time of Australian Wildfires Estimated by Fire Management Personnel”. *International Journal of Wildland Fire*, 21(3): pp. 219–229.
- Prestemon, Jeffrey P. et al. (2008). *Economically Optimal Wildfire Intervention Regimes*. Chicago, IL: American Agricultural Economics Association Annual Meeting.
- Quinn, Beth (2005). “Monster in the Woods: The Biscuit Fire”. *Fire Management Today*, 65(2): pp. 4–18.
- Radeloff, Volker C et al. (2005). “The Wildland-Urban Interface in the United States”. *Ecological Applications*, 15(3): pp. 799–805.
- Reitzes, James D. and Oliver R. Grawe (1999). “Entry Policy and Entry Subsidies”. *Review of International Economics*, 7(4): pp. 715–731.
- Roodman, David (2006). *How to do xtabond2: An Introduction to Difference and System GMM in Stata*. Working Paper 103. Center for Global Development.
- Santarelli, E. and M. Vivarelli (2002). “Is Subsidizing Entry an Optimal Policy?” *Industrial and Corporate Change*, 11(1): pp. 39–52.
- Schoennagel, Tania, Thomas T Veblen, and William H Romme (2004). “The Interaction of Fire, Fuels, and Climate Across Rocky Mountain Forests”. *BioScience*, 54(7): pp. 661–676.
- Service, US Forest (2011). *Wildland Fire Decision Support System*. URL: <http://wfdss.usgs.gov>.

- Shumway, Tyler (2001). "Forecasting Bankruptcy More Accurately: A Simple Hazard Model". *The Journal of Business*, 74(1): pp. 101–124.
- Sparhawk, W. N. (1925). "Use of liability ratings in forest protection". *Journal of Journal of Agricultural Research*, 30, pp. 693–792.
- Spencer, Barbara J. and James A. Brander (1983). "International R&D Rivalry and Industrial Strategy". *The Review of Economic Studies*, 50(4): pp. 707–722.
- Stephens, Scott L and Lawrence W Ruth (2005). "Federal Forest-Fire Policy in the United States". *Ecological Applications*, 15(2): pp. 532–542.
- Stokes, Leah C (2013). "The Politics of Renewable Energy Policies: The Case of Feed-in Tariffs in Ontario, Canada". *Energy Policy*.
- Strauss, D., L. Bednar, and R. Mees (1989). "Do One Percent of the Forest Fires Cause Ninety-Nine Percent of the Damage?" *Forest Science*, 35(2): pp. 319–328.
- Triplett, J.E. (1999). *Measuring the Prices of Medical Treatments*. Brookings Institute Press.
- Troyer, Jack et al. (2003). *Large Fire Cost Reduction Action Plan*. USDA Forest Service, USDI, and the National Association of State Foresters. URL: http://www.fs.fed.us/fire/ibp/cost_accounting/5100_LargeFireCostReductionAction_Mar_03.pdf.
- Ulph, Alistair (1996). "Environmental Policy and International Trade when Governments and Producers Act Strategically". *Journal of Environmental Economics and Management*, 30(3): pp. 265–281.
- USDOT (2005). "Miles of roads by type and county". U.S. Department of Transportation.
- Westerling, Anthony L et al. (2006). "Warming and Earlier Spring Increase Western US Forest Wildfire Activity". *Science*, 313(5789): pp. 940–943.
- Whalley, John (1991). "The Interface Between Environmental and Trade Policies". *The Economic Journal*, 101(405): pp. 180–189.
- Wienke, Andreas et al. (2005). "A Comparison of Different Bivariate Correlated Frailty Models and Estimation Strategies". *Mathematical Biosciences*, 198(1): pp. 1–13.

- Wilson, John D. (1999). “Theories of Tax Competition”. *National Tax Journal*, 52(2): pp. 269–304.
- Windmeijer, Frank (2005). “A Finite Sample Correction for the Variance of Linear Efficient Two-Step GMM Estimators”. *Journal of Econometrics*, 126(1): pp. 25–51.
- Winkelmann, R. (2000). “Seemingly Unrelated Negative Binomial Regression”. *Oxford Bulletin of Economics and Statistics*, 62(4): pp. 553–560.
- Yoder, Jonathan (2010). *Differences in wildfire outcomes in the United States across space, fire causes, and suppression strategies*. Tech. rep. Submitted to the US Forest Service under Cooperative Agreement SRS 07-CA-11330143-077. Washington State University.
- Yoder, Jonathan and Krista Gebert (2012). “An Econometric Model for *ex ante* Prediction of Wildfire Suppression Costs”. *Journal of Forest Economics*, 18(1): pp. 76 –89.
- Zodrow, George R and Peter Mieszkowski (1986). “Pigou, Tiebout, Property Taxation, and the Underprovision of Local Public Goods”. *Journal of Urban Economics*, 19(3): pp. 356–370.