Resource Allocation Under Fire*

Jude Bayham† Jonathan K. Yoder‡

May 5, 2015

Abstract

Rising suppression cost and severity of wildfires in the US has prompted debate over federal wildfire management policy. The empirical economic literature on wildfire has sought to identify the factors that contribute to wildfire growth and cost without directly modeling the role of resource allocation over the course of the fire. Without a model of suppression resource allocation, it is difficult to understand how policy will impact wildfire outcomes. We fill this gap in the literature by estimating an econometric model of suppression resource allocation, wildfire expenditures, growth, and home damage using a dynamic panel dataset on over 500 wildfires in the Western U.S. Our econometric model is grounded in a theory of resource allocation that shows how individual fire managers communicate their need for resources to a regional command unit through the resource's shadow price. This model allows us to parse the complex incentives of wildfire managers, and disentangle direct from indirect impacts of threatened assets, environmental conditions, and resource scarcity on wildfire expenditure, growth, and damage. Among other results, we find that the use of aircraft increases daily wildfire expenditures by 35% while highly trained ground crews mitigate the daily damage to threatened homes.

Selected Paper prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, CA, July 26-28

 This research was funded by Cooperative Agreement RWU-FS-SRS-4804 U.S.D.A. Forest Service Southern Research Station, and the Washington State University Agricultural Research Center project #0544.

†Yale School of Forestry and Environmental Studies, jude.bayham@yale.edu.

‡School of Economic Sciences, Washington State University, yoder@wsu.edu

1 Introduction

For the past century, wildland fire has been one of the most common and costly natural disasters in the U.S. Suppression costs have increased over the last couple of decades to the point where the federal government routinely spends over one billion dollars per year managing active wildfires (NIFC, 2014). The recent escalation of wildfire management cost has focused the attention of policy-makers and researchers on the factors that contribute to large expensive wildfires. While, there is a growing literature on wildfire cost and size (Gebert et al., 2008; Abt, Prestemon, and Gebert, 2009; Yoder and Gebert, 2012), few studies focus on the important role of emergency resource allocation and the incentives faced by managers during a response effort. The objective of this study is to develop a theoretical and empirical framework to analyze emergency resource allocation over the course of a suppression effort and quantify the subsequent impact of those decisions on policy-relevant outcomes.

We develop a model of wildfire response that explicitly incorporates the interaction between fire managers and regional command units.[1] We then develop and estimate an econometric model of wildfire expenditures, growth, and damage to homes with endogenous resource allocation. The model enables us to identify the causal effect of economic and environmental conditions on relevant wildfire outcomes. Thus, we are able to parse the direct effect of environmental conditions such as weather on wildfire growth from the indirect effect of weather on resource allocation, which affects wildfire growth.

Several studies have documented the connection between the growing wildland ur-

[1]The 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.

ban interface (WUI) and recent increases in wildfire growth and expenditures (Gude et al., 2013; Yoder and Gebert, 2012). Simulation studies, such as Fried, Gilless, and Spero (2006), suggest that an emphasis on home protection diverts firefighting resources away from containment efforts leading to larger fires. Yet, this hypothesis has not been tested using observed data on firefighting resource allocation. We exploit a dynamic panel dataset on wildfires in the Western US from 2003-2010 and show that resources adept at home protection are dispatched to a fires with more threatened homes while other resources respond to expected fire growth. This evidence reveals that protection of homes is an important objective of fire managers but also implies dynamic feedbacks between the evolution of the fire and firefighting resource allocation.

Individual fire managers face a complex set of objectives throughout the course of a fire (Calkin et al., 2013). Fire managers, operating in an uncertain environment, accumulate information and develop, implement and update management plans over the course of a fire. When multiple wildfires are burning within a region, a regional command unit allocates response resources between fires. 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; Mercer et al., 2007). 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. In this setting, fire managers compete for resources allocated through the central dispatch center by conveying the "need" or usefulness of firefighting resources for application to their fire at a particular time. Abstractly, this is equivalent to and modeled as conveying the shadow value of resources for a fire, which the central dispatch compares to shadow prices for those resources for other fires as conveyed by competing fire managers. Our model yields a set of structural equations from which we derive a set of estimable reduced-form resource allocation equations.

Wildfires are numerous but occur over a period of time such that frequent and detailed data can be collected on actions taken and wildfire outcomes. However, most empirical studies of wildfire outcomes rely on data aggregated over a fire, or even an entire fire season (Liang et al., 2008; Prestemon and Donovan, 2008; Yoder and Gebert, 2012).[2] The few studies that have used micro-level panel data to study wildfire outcomes do not include resource allocation (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 expenditures and growth, but are unable to identify the policy-relevant mechanisms by which environmental and economic factors impact observed wildfire outcomes.

Our results have direct policy implications. We find that resource allocation is influenced by emerging threats to property and expectations about future fire behavior. For instance, fires with extreme growth potential receive additional aircraft, which raises daily expenditure by over 35%. In contrast, threatened homes encourage the dispatch of highly trained ground crews and engines, which reduce damage to threatened homes. While the actions of these resources can significantly influence wildfire outcomes, environmental factors such as temperature, precipitation, and wind still pose risks that cannot be completely controlled. These results highlight the importance of modeling the dynamic feedback between management decisions and wildfire

[2] Another class of studies construct models of wildfire response, and simulate response strategies (Fried, Gilless, 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.

outcomes.

The remainder of the paper is outlined as follows. Section 2 develops a model of wildfire response to explicitly characterize the interaction between individual fire managers and a regional command unit. Section 3 describes the data and econometric model of daily wildfire growth, expenditures, and damage to homes. Section 4 presents the results and section 5 provides a discussion of the policy implications.

2 Model

Consider an individual fire manager that allocates response resources over the course of a single 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 firefighting resources to the regional command unit through its shadow price. The regional command unit aggregates this information and allocates a finite set of firefighting resources to each fire such that the marginal value of an additional resource is equal across all simultaneously burning fires.

We model wildfire response over the course of a fire as a two-period problem in order to clarify the interaction between individual wildfire managers and their regional command units, as well as the highlight the feedbacks between human intervention and fire growth. In the first period, threatened assets are identified and available firefighting resources are allocated by the incident commander. In the following period, the damage and growth of the fire is realized and is considered sunk by the incident commander. This two-period model is consistent with our dataset and is useful for our empirical identification strategy. Sections 2.1 and 2.2 describe the individual fire manager's and regional command unit's problems, respectively.

2.1 Wildfire Manager

Fire managers face complex tradeoffs. They do not own the resources that they are protecting. Instead, these assets are often owned by numerous private owners or managed by public agencies. Nor do fire managers face the costs of firefighting, which are fiscally borne by the agency for whom he or she works.[3] Nonetheless, they are responsible for allocating scarce firefighting resources, often under emergency conditions in which timeliness is crucial. Under these conditions, fire manager decisions are based on their preferences and a complex set of indirect incentives, including employment consequences, political pressure, and legal threats. We model the fire manager as a loss minimizer, where the loss function is specified in general terms as

$$\ell_t(d_t, c_t). \tag{1}$$

Loss at time t is increasing in damages, d_t, and expenditures, c_t realized at time t. This general specification of the objective function allows 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 expenditures and damage. Expenditures on response are

$$c_t = \mathbf{y}_t'\mathbf{w}, \tag{2}$$

[3] Donovan 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 recognize the lack of a true budget constraint in a choice experiment study of wildfire manager incentives.

where $\mathbf{y}_t$ is the $(J \times 1)$ vector of firefighting resources allocated in time t and $\mathbf{w}$ is the $(J \times 1)$ vector of corresponding prices. Resource prices include wages for firefighters and the rental rate of capital assets such as dozers and aircraft. These prices are generally arranged prior to the beginning of the response effort and are assumed fixed over the duration of the fire.

Wildfire damage is realized in the second period and is

$$d_{t+1} = d(\mathbf{v}_t, \mathbf{y}_t, a_{t+1}(\mathbf{y}_t, \mathbf{p}_{t+1}) + \varepsilon^a_{t+1}) + \varepsilon^d_{t+1}, \tag{3}$$

where damage is an increasing function of a $(K \times 1)$ vector of threatened assets at time t, $\mathbf{v}_t$, a decreasing function of firefighting resources allocated at time t, $\mathbf{y}_t$, and an increasing function of fire growth over the interval $\{t, t+1\}$, $a_{t+1}(\cdot)$, which itself is a decreasing function of currently assigned firefighting resources and a vector of exogenous environmental and geographic characteristics over the interval $\{t, t+1\}$, $\mathbf{p}_{t+1}$. Damage in $t+1$ depends on firefighting actions and environmental conditions, both of which are uncertain. Uncertainty with regard to environmental conditions is captured by a mean zero random variable ε^a_{t+1}. The effectiveness of the firefighting resources is idiosyncratic and captured by the mean zero random variable ε^d_{t+1}.

The vector of threatened asset values may include homes and other private structures, watersheds, harvestable timber, and wildlife habitat. Response resources reduce damage through two channels: 1) by taking actions to protect specific threatened assets reducing the likelihood that they burn, and 2) by mitigating the growth of the fire. 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 complement the efforts to suppress fire growth. (Hirsch and Martell, 1996; Plucinski et al., 2012).

The fire manager allocates the resources available to him or her at time t. The resources are dispatched by regional command unit at the beginning of time t creating a short term constraint, $\bar{\mathbf{y}}_t \geq \mathbf{y}_t$. The resource constraint and the associated Lagrange multiplier in the constrained optimization problem serve as the point of connection between the individual fire manager and the regional command unit.

In each planning period, the fire manager develops a strategy, $\mathbf{y}_t$, to solve

$$L_t = \left\{ \min_{\mathbf{y}_t \geq \mathbf{0}} \; \ell_t(c_t, d_t) + E_t \left\{ \ell_{t+1}(c_{t+1}, d_{t+1}) \right\} : \text{ s.t. } \; \bar{\mathbf{y}}_t \geq \mathbf{y}_t \right\} \tag{4}$$

where $\ell_t(\cdot)$, c_t, and d_t are defined in equations, (1), (2), and (3), respectively. Equation (4) states that fire managers allocate a constrained set of firefighting resources at time t to minimize contemporaneous and expected losses. Damage at time t is a function of past allocation decisions and the realization of a random variable and is effectively exogenous at time t. However, expenditures at time t are a function of firefighting resources allocated at time t, which reduce expected losses in $t+1$ through expected damage. The expectation is conditional on the information set at time t.

The first order conditions of the fire manager's minimization problem are

$$\begin{aligned} & Z_{\mathbf{y}_t} \equiv \frac{\partial \ell_t}{\partial c_t} \mathbf{w} + E_t \left[\frac{\partial \ell_{t+1}}{\partial d_{t+1}} \left(\frac{\partial d_{t+1}}{\partial \mathbf{y}_t} + \frac{\partial d_{t+1}}{\partial a_{t+1}} \frac{\partial a_{t+1}}{\partial \mathbf{y}_t} \right) \right] - \boldsymbol{\lambda}_t = \mathbf{0}; \\ & \mathbf{y}_t \geq \mathbf{0}; \;\; \bar{\mathbf{y}}_t \geq \mathbf{y}_t; \;\; \boldsymbol{\lambda}_t \geq \mathbf{0}; \;\; Z_{y_{i,t}} y_{j,t} = 0 \text{ and } \lambda_{j,t}[\bar{y}_{j,t} - y_{j,t}] = 0 \quad \forall \, j, \end{aligned} \tag{5}$$

where $\lambda_{j,t}$ is the Lagrangian multiplier of firefighting resource j at time t. Equation (5) is a $(J \times 1)$ vector where for each firefighting resource: the first term is positive and captures the losses due to increasing expenditures, the bracketed term is negative and captures the expected reduction in future losses from allocating more resources today,[4]

[4]The expected marginal damage reduction of resource j, $\frac{\partial d_{t+1}}{\partial \mathbf{y}_t}$, captures the sum of mitigated

and multiplier is positive and captures the net marginal benefit of an additional unit of response resource j at time t.[5] This system of equations implicitly defines an equilibrium at time t, $\{\mathbf{y}_t^*(\bar{\mathbf{y}}_t; \mathbf{x}_t), \boldsymbol{\lambda}_t^*(\bar{\mathbf{y}}_t; \mathbf{x}_t)\}$, for each planning period where $\mathbf{x}_t = \{\mathbf{v}_t, \mathbf{p}_{t+1}, \mathbf{w}\}$. This model describes a range of wildfire scenarios from the case in which threatened assets justify large firefighting efforts to the case where few or no assets are at risk leading to little or no response.

2.2 Regional Command Unit

The federal contract for securing firefighting resources states that resource are assigned based on "best value" conditional on meeting a minimum set of requirements (NIFC, 2011). In the context of our model, "best value" refers to the largest net marginal benefit of receiving an additional resource of all individual fire managers. Individual fire managers communicate their need for response resources to the regional command unit through the shadow price λ_{ji} for each resource $j = 1, \ldots, J$ and fire $i = 1, \ldots, I$. Once resources are committed to a fire, they remain committed for the entire planning period (e.g., a day), after which they may be reassigned to another fire. While tactics and strategies may vary idiosyncratically across individual fire managers, their primary objectives remain consistent. We assume that the regional command unit knows the loss function of each individual fire manager and the information set over which expectations are formed.

The regional command unit chooses I sets of J resources to minimizes the sum of

damage across all assets threatened at time t, $\mathbf{v}_t$.

[5] The resource constraint is binding only when the manager would use the additional resource, i.e., the marginal benefit exceeded the marginal cost. In equilibrium, λ is equal to the expected marginal benefit less costs, which can be positive or zero when the constraint is not binding.

expected losses across all wildfires I burning during time t,

$$\min_{\bar{\mathbf{y}}_{i,t}} \sum_{i=1}^{I} L_{i,t}(\bar{\mathbf{y}}_{i,t}; \mathbf{x}_{i,t}) : \quad \text{s.t.} \quad \bar{\bar{\mathbf{y}}}_t \geq \sum_{i=1}^{I} \bar{\mathbf{y}}_{i,t}, \tag{6}$$

where $L_{i,t}(\cdot)$ is the indirect loss function of fire manager i at time t defined in equation (4) and $\bar{\bar{\mathbf{y}}}_t$ denotes the constraint on resources available to the region at any given point in time. This resource constraint may follow from a budget constraint, or because of the importance of timeliness, and shortages imposed by insufficient pre-season preparedness and resource contracts and acquisition. Wildfires begin and end throughout the year, so the regional command unit repeatedly solves this minimization problem in each planning period. For simplicity, we assume that once pre-season investments are made, the regional command unit does not plan for or attempt to predict the spatiotemporal distribution of new fire ignitions, but does consider them once ignited. The regional command unit and individual fire managers share the same information set and thus, form the same expectations about future wildfire outcomes embedded in $L_{i,t}(\cdot)$. The first-order conditions of the regional command unit's problem are

$$\begin{aligned} R_{i,t} \equiv \frac{\partial L_{i,t}(\bar{\mathbf{y}}_{i,t}; \mathbf{x}_{i,t})}{\partial \bar{\mathbf{y}}_{i,t}} = \boldsymbol{\mu}_t; \quad \bar{\mathbf{y}}_{i,t} \geq \mathbf{0}; \quad \bar{\mathbf{y}}_{i,t} R_{i,t} = 0 \quad \forall\, i \\ \bar{\bar{\mathbf{y}}}_t - \sum_{i=1}^{I} \bar{\mathbf{y}}_{i,t} \geq \mathbf{0}; \quad \mu_{j,t} \left[\bar{\bar{y}}_{j,t} - \sum_{i=1}^{I} \bar{y}_{i,j,t} \right] = 0; \quad \mu_{j,t} \geq 0 \quad \forall\, j, \end{aligned} \tag{7}$$

where $\boldsymbol{\mu}_t$ is a $(J \times 1)$ vector of shadow prices corresponding to each resource type. Equation (7) implies that in equilibrium, the net marginal benefit of an additional resource, $\bar{y}_{i,j,t}$, which is equal to the individual fire manager's shadow price, $\lambda_{i,j,t}$,[6] is

[6]Differentiating (4) with respect to the constraint, $\bar{\mathbf{y}}_t$, yields $\boldsymbol{\lambda}'_t$ both prior to and after optimization. This result implies that $\frac{\partial L_{i,t}}{\partial \bar{y}_{i,j,t}} \equiv \lambda_{i,j,t}$ even out of equilibrium.

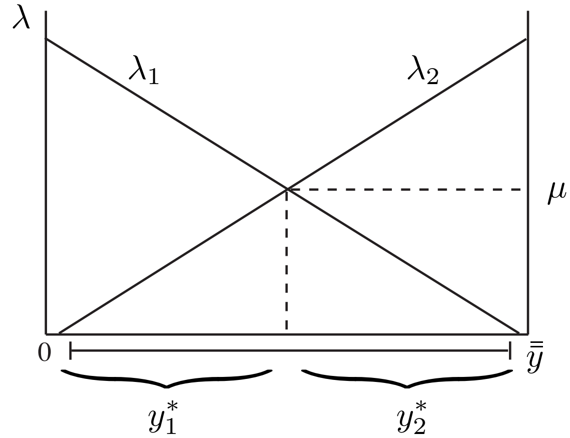

Figure 1: Regional Command Unit's Problem.

equal to the regional command unit's shadow price of the resource $\mu_{j,t}$. This condition implies that the regional command unit strives to allocate resources efficiently by equating the net marginal benefit of each resource j across all fires i at time t, i.e., $\frac{\partial L_{i,t}}{\partial \bar{y}_{i,j,t}} = \lambda_{i,j,t} = \mu_{j,t}$ for all i, j, and t.

We illustrate the equilibrium condition with an example of two concurrently burning fires in Figure 1. The regional command unit allocates a single resource, $\bar{\bar{y}}$, across Fire 1 and Fire 2. Fire 1's marginal benefit, λ_1 is decreasing in $\bar{y}_1$, while Fire 2's marginal benefit, λ_2, is increasing in $\bar{y}_1$ (and decreasing in $\bar{y}_2$). The optimal allocation of $\bar{\bar{y}}$ occurs where $\mu = \lambda_1 = \lambda_2$. 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 $\mu = 0$ (each fire receives the resources requested). If, in contrast, a Fire 1 requested more resources than available, $\mu = \lambda_1$ at the vertical intercept.

2.3 Resource Allocation Equations

The optimal allocation of resources within any fire i is $\mathbf{y}^*_{i,t}(\bar{\mathbf{y}}_{i,t};\mathbf{x}_{i,t})$ with equilibrium shadow price $\boldsymbol{\lambda}^*_{i,t}(\bar{\mathbf{y}}_{i,t};\mathbf{x}_{i,t})$. Substituting the equilibrium vector of shadow prices into the first order condition of the regional command unit's problem (equation (7)) yields a system of $(I+1)*J$ equations in $(I+1)*J$ unknowns $(\bar{y}_{i,j},\mu_j)$

$$
\begin{aligned}
\lambda^*_{1,1,t}(\bar{\mathbf{y}}_{1,t};\mathbf{v}_{1,t},\mathbf{p}_{1,t+1},w_{1,1}) &= \mu_{1,t}\\
\lambda^*_{1,2,t}(\bar{\mathbf{y}}_{1,t};\mathbf{v}_{1,t},\mathbf{p}_{1,t+1},w_{1,2}) &= \mu_{2,t}\\
&\vdots\\
\lambda^*_{I,J,t}(\bar{\mathbf{y}}_{I,t};\mathbf{v}_{I,t},\mathbf{p}_{I,t+1},w_{I,J}) &= \mu_{J,t}\\
\sum_{i=1}^{I}\bar{y}_{i,1,t} &= \bar{\bar{y}}_{1,t}\\
&\vdots\\
\sum_{i=1}^{I}\bar{y}_{i,J,t} &= \bar{\bar{y}}_{J,t} \quad \forall \;\; t.
\end{aligned} \tag{8}
$$

The solution to the system of equations yields the optimal allocation of J resources to each fire $\{\bar{\mathbf{y}}^*_i\}_{i\in I}$. At any point during the management effort, the quantity of resource j dispatched to fire i is a function of expected conditions on fire i as well as expected conditions on all other fires $-i$ burning within the region. Equations (8) imply the following reduced-form equations

$$
\bar{y}_{i,j,t} = \bar{y}_j(\overbrace{\mathbf{w}_i,\mathbf{v}_{i,t},\mathbf{p}_{i,t+1}}^{Demand\ \ Factors},\overbrace{\bar{\bar{\mathbf{y}}}_{j,t},\mathbf{w}_{-i},\mathbf{v}_{-i,t},\mathbf{p}_{-i,t+1}}^{Supply\ \ Factors},\varepsilon^y_{i,j,t}) \quad \forall \; i,j, \tag{9}
$$

where $\bar{y}_j(\cdot)$ denotes the unique resource allocation function for each type of resource j, and $\varepsilon^y_{i,j,t}$ captures unobserved heterogeneity. The unobserved heterogeneity includes a fire-specific component that captures unique feature of a particular fire or management strategy, and a time-varying component that captures unobserved daily characteristics of the fire. The conditions on fire i influence the demand for resources while the same conditions on fires $-i$ influence the supply of resources because all concurrently burning fires compete for a finite set of resources. In reality, the conditions on each of the other concurrent fires may have variable impacts on fire i. However, an econometric model must be specified consistently across all fires. We sum the number of threatened homes on all other fires and assume that weather conditions are correlated within a region. Equation (9) provides a structural link between threatened assets, environmental conditions, and resource allocation while the underlying model provides the intuition for how threatened assets and environmental conditions impact resource allocation.

2.4 Wildfire Growth, Expenditures, and Damage

Ultimately policy makers are interested in the factors that increase wildfire size, expenditures, and damage. However, parsing the effect of firefighting actions and environmental conditions is challenging. Our two-stage model of wildfire response provides a structural foundation for a set of estimable equations of wildfire growth, expenditures, and damage. Substituting the equilibrium resource allocation, $\mathbf{y}^*_{i,t}(\bar{\mathbf{y}}^*_{i,t};\mathbf{x}_t)$ back into the fire growth, expenditure, and damage functions yields

$$a_{i,t} = a(\mathbf{y}^*_{i,t-1}, \mathbf{p}_{i,t}) + \varepsilon^a_{i,t} \tag{10a}$$

$$c_{i,t} = \mathbf{y}^{*\prime}_{i,t}\mathbf{w}_i + \varepsilon^c_{i,t} \tag{10b}$$

$$d_{i,t} = d(\mathbf{y}^*_{i,t-1}, a(\mathbf{y}^*_{i,t-1}, \mathbf{p}_{i,t}) + \varepsilon^a_{i,t}) + \varepsilon^d_{i,t}, \tag{10c}$$

where $\varepsilon^a, \varepsilon^c, \varepsilon^d$ are equation-specific disturbances. The growth and damage disturbances are described in equation (3). The disturbance in the expenditure equation, ε^c, follows from the unobserved heterogeneity not captured by the resource allocation model. The timing of the model informs the use of lagged resource allocations in the growth and damage equations (10a) and (10c). The following section describes the data and the empirical model used to estimate equations (9, 10a, 10b, 10c).

3 Data and Empirical Methods

The data used in this study are compiled from several publicly available datasets. Dynamic panel data on wildfire outcomes, resources used, and conditions are based on daily Incident Status Summary reports (ICS-209) completed by incident commanders over the course of the fire (FAMWEB, 2012). Ignition-point and final summary data come from National Interagency Fire Management Integrated Database (NIFMID) (KCFAST, 2012). County- and climate division-level weather conditions are collected from the National Oceanic and Atmospheric Administration, National Climate Data Center (NOAA, 2014). Additional housing data is collected from the US Census (United States Census Bureau, 2011). Table 1 contains the data sources and a brief description of the data gathered from each source. Table 2 contains summary statistics of the variables used in the analysis.

Table 1: Variable Descriptions and Source Information of Compiled Dataset

Datasets	
(ICS-209) SIT Reports	Time-varying wildfire data 2003-2010 (FAMWEB, 2012)
NIFMID Reports	Summary wildfire data 2003-2010 (KCFAST, 2012)
NOAA NCDC	Weather and drought data by county 2003-2010 (NOAA, 2014)
U.S. Census	Housing and urban data 2010 (United States Census Bureau, 2011)

Variable name	Brief description and source
`Crew 1`	Number of type 1 crew firefighters (ICS box 43)
`Crew 1`$_{-i}$	Number of type 1 crew firefighters on all other fires $-i$ (ICS box 43)
`Crew 2`	Number of type 2 crew firefighters (ICS box 43)
`Crew 2`$_{-i}$	Number of type 2 crew firefighters on all other fires $-i$ (ICS box 43)
`Aircraft`	Number of type 1, 2, and 3 helicopters (ICS box 43)
`Aircraft`$_{-i}$	Number of type 1, 2, and 3 helicopters on all other fires $-i$ (ICS box 43)
`Dozer`	Number of bulldozer and tractor plow crew persons (ICS box 43)
`Dozer`$_{-i}$	Number of bulldozer and tractor plow crew persons on all other fires $-i$ (ICS box 43)
`Engine`	Number of engine and water tender crew persons (ICS box 43)
`Engine`$_{-i}$	Number of engine and water tender crew persons on all other fires $-i$ (ICS box 43)
`lnCost`	Natural log of suppression expenditure to date (ICS box 19) in dollars.
`lnArea`	Natural log of the total area burned to date (ICS box 15) in acres.
`Damaged Homes`	Number of residential structures damaged and destroyed (ICS box 24).
`Threatened Homes`	Number of residential structures threatened (ICS box 24).
`Threatened Homes`$_{-i}$	Number of residential structures threatened on all other fires $-i$ (ICS box 24).
`Count` (I)	Number of other fires $-i$ burning in the region within the past 48 hours
`Growth`	Subjective measure of future fire behavior {Low, Medium (baseline), High, Extreme} (ICS box 39a)

continued

	continued
Variable name	Brief description and source
`Inaccess`	Subjective measure of access difficulty based on terrain {Low & Medium (baseline), High, Extreme} where extreme is most difficult (ICS box 39b)
`lnMedValue`	Natural log of county-level median home value in which the fire began (Census).
`lnDistance`	Natural log of distance from ignition to nearest Census Designated Place (Census).
`Hdensity20`	Distance weighted home density within 20 miles of ignition point (Census).
`Wind`	Average reported windspeed in mph over current operational period (ICS box 30).
`Temperature`	Mean daily maximum temperature in county where ignited in Fahrenheit (NOAA).
`Relative Humidity`	Average reported relative humidity on scale of $0 - 100$ over current operational period (ICS box 30).
`Precipitation`	Mean daily precipitation in county where ignited in inches (NOAA).
`PDSI`	Average monthly Palmer Drought Severity Index matched at climate division (NOAA).
`Percent Contained`	Subjective estimate of containment (ICS box 16).
`Day of Year`	Report date (ICS box 1) converted into radians and transformed with sine cosine functions.
`Year`	Categorical variable for each year (baseline=2004).
`FS Region`	Categorical variable for each USFS region in the Western US {North (MT, ND, N.ID), Southwest (AZ, NM), Intermountain (NV, UT, S.ID), Rocky Mountain (WY, CO, KS, NE, SD), Pacific Southwest (CA), Pacific Northwest (WA, OR) [baseline] }.
`Lightning`	Binary equal to 1 if wildfire was caused by lightning (baseline=human) (ICS box 8).
`Fuel Model`	NFDRS fuel models Timber (baseline)= {H, R, E, P, U, G}, Grass= {A, L, S, C, T, N}, Brush= {F, Q, B, O}, Slash= {J, K, I} (NIFMID).
`Slope`	Percent grade of slope at point of ignition (NIFMID).
`Elevation`	Elevation in thousands of feet at point of ignition (NIFMID).
`Wilderness`	Binary equal to 1 if fire was ignited on land designated for wilderness management (NIFMID).

Table 2: **Summary Statistics for Wildfires in Western U.S 2003-2010**

	Obs.	Mean	Std. Dev.	Min	Max
Crew 1	2,800	130.82	199.12	0	1,337
Crew 1_{-i}	2,800	106.87	1,434.29	0	28,346
Crew 2	2,800	79.15	106.49	0	2,011
Crew 2_{-i}	2,800	10.75	161.13	0	3,864
Aircraft_{-i}	2,800	5.08	5.79	0	47
Aircraft_{-i}	2,800	0.27	2.78	0	91
Dozers	2,800	14.18	23.44	0	348
Dozers_{-i}	2,800	0.41	6.47	0	152
Engines	2,800	158.49	214.08	0	1,448
Engines_{-i}	2,800	8.89	73.33	0	1,151
Cost	2,748	457,270	1,934,820	1	80,700,000
Area	2,800	1,696	5,065	1	135,000
Damaged Homes	841	3.02	33.39	0	613
Threatened Homes	2,800	279.55	1,811.46	0	55,000
Threatened Homes_i	2,800	145.32	1,921.38	0	34,500
Count (I)	2,800	6.74	4.56	1	31
Growth Potential Low	2,799	0.12	0.33	0	1
Growth Potential High	2,799	0.43	0.49	0	1
Growth Potential Extreme	2,799	0.21	0.41	0	1
Inaccessibility High	2,800	0.38	0.49	0	1
Inaccessibility Extreme	2,800	0.51	0.50	0	1
MedVal	2,800	237,570	149,143	27,862	685,700
Distance	2,800	14.45	9.26	0	59
Hdensity20	2,800	192.40	229.61	0	1,309
Temperature	2,800	86.24	9.20	42	114
Precipitation	2,800	0.01	0.05	0	1.19
Wind	2,800	9.67	7.13	0	86
Relative Humidity	2,800	25.35	15.38	3	100
Palmer Drought Index	2,800	-2.05	2.19	-7.49	10.35
Percent Contained	2,800	31.45	29.01	0	100
Day of Year	2,800	218.55	38.99	37	339
Year 2003	2,800	0.18	0.39	0	1
Year 2004	2,800	0.08	0.27	0	1
Year 2005	2,800	0.08	0.27	0	1
Year 2006	2,800	0.21	0.41	0	1
Year 2007	2,800	0.23	0.42	0	1
Year 2008	2,800	0.13	0.33	0	1

continued

	Obs.	Mean	Std. Dev.	Min	Max
Year 2009	2,800	0.05	0.22	0	1
Year 2010	2,800	0.04	0.19	0	1
FS Region North	2,800	0.22	0.41	0	1
FS Region Southwest	2,800	0.15	0.36	0	1
FS Region Intermountain	2,800	0.13	0.34	0	1
FS Region Pac. Southwest	2,800	0.28	0.45	0	1
FS Region Rocky Mountain	2,800	0.04	0.20	0	1
FS Region Pac. Northwest	2,800	0.18	0.38	0	1
Fuel Model Timber	2,800	0.62	0.48	0	1
Fuel Model Grass	2,800	0.18	0.38	0	1
Fuel Model Brush	2,800	0.16	0.36	0	1
Fuel Model Slash	2,800	0.04	0.20	0	1
Slope	2,800	42.32	24.68	0	100
Elevation	2,800	5,232.76	2,221.61	160	10,000
Wilderness	2,800	0.24	0.42	0	1

The ICS-209 data contain the number of response resources $y = \{$Type 1 Crews, Type 2 Crews, Aircraft, Dozers, and Engines$\}$ committed to fire i by agency. We aggregate resources allocated over agency because regional command units coordinate the distribution of units amongst various agencies during large fires. We then aggregate over groups of similar resources (e.g., engines and water tenders are aggregated to form the variable Engine). We do not aggregate Type 1 and 2 firefighting crews because of a significant difference in training, autonomy, and expected productivity.[7]

Incident commanders report the number of single resources and strike teams of each resource type.[8] Moreover, engines and dozers require crews to operate. We combine single resources and strike teams into a single measure of resources dispatched to reduce the number of highly correlated regressors. We estimate a fixed effects regression of total active persons on the single resource and strike team resources to

[7]Type 1 crews are usually full-time employees with high-level training, whereas type 2 crews are often comprised of seasonal firefighters with limited training.

[8]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.

derive appropriate weights for combining the two sets of variables.[9] The results are presented in the Supplementary Material. The regression coefficients represent the number of firefighters associated with each resource reportedly dispatch to the fire. We adopt this approach because ignoring the crew would underestimate the resource's contribution to daily expenditures.

Wildfire suppression expenditures and size are reported in the ICS-209. We observe wildfire expenditures and size as frequently as ICS-209 reports are filed, which are generally daily but can be more or less frequent depending on activity. We normalize the change in wildfire expenditures and size (growth) to daily outcomes by dividing the change by the duration between reports. Daily growth and expenditures are both log transformed as in Yoder and Gebert (2012). We omit observations where the fire is reported as 100% contained. We include only fires managed under full suppression to exclude instances where the fire is purposely left to burn. We limit our analysis to fires in the Western U.S. (Forest Service Regions: North, Intermountain, Rocky Mountain Pacific Northwest, Pacific Southwest, and Southwest) because wildfire management conditions and strategies in the South differ from the West. The ICS-209 expenditures data have been criticized for inaccuracies and inconsistent reporting when compared with the NIFMID final fire outcomes (Gude et al., 2013; Gebert, Calkin, and Yoder, 2007). However, 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.

The count of homes threatened, damaged, and destroyed are reported in each planning period. Damage is the sum of damaged and destroyed homes in each plan-

[9] When resource j data is missing at time t within a fire for which other resource $-j$ data is nonmissing, 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.

ning period. Fire managers also report the expected wildfire behavior in a categorical variable, Growth Potential. The variables Threatened Homes and Growth Potential closely capture potential damage, d_{t+1}, and expected fire growth, a_{t+1}, developed in the theory.

Weather and environmental conditions influence wildfire behavior and thus, resource allocation. The ICS-209 data contain temperature, wind speed, and relative humidity reported by the incident commander at the time the report is completed. We verify the ICS-209 records and fill in missing data with daily county-level maximum temperature, average wind speed, maximum relative humidity from the National Oceanic and Atmospheric Administration, National Climate Data Center (NOAA, 2014). We also include mean daily precipitation from NOAA. We use these weather data as instruments for expected fire growth and to control for exogenous variation in the second-stage fire growth and damage regression equations (equations (10a) and (10c)). We supplement the ICS-209 data with environmental and geographic ignition-point data from the NIFMID. The ICS-209 and NIFMID data contain many of the same fires but share no common identifier that would facilitate a simple merging of the two datasets. We develop an algorithm to match fires from both datasets based on an index comprised of fire name, location, expenditures, size, and start date. A detailed description of the algorithm is in Supplementary Material.

The resource allocation equations (9) imply that the resources committed to fire i depend on the same conditions that affect all fires $-i$ within the region. We construct a measure of conditions on fires $-i$ by aggregating the conditions across all wildfires burning in the region within the past 48 hours. Details of the algorithm can be found in Supplementary Material. We use this aggregation method to construct the total number of resource$_j$ committed to other fires $-i$, count the number of other fires $-i$, and sum the number of threatened homes on fires $-i$.

3.1 Econometric Model

We use a dynamic panel model, commonly referred to as the Arellano-Bond (AB) systems estimator (Arellano and Bover, 1995; Blundell and Bond, 1998), to estimate daily wildfire growth and expenditures with endogenous resource allocation. The AB model uses the dynamic structure of the panel to find internal instruments for endogenous regressors (response resources). Moreover, the estimator is robust to within-panel serial correlation and heteroskedasticity. Damage is reported in terms of the number of homes damaged and destroyed. Homes cannot be damaged unless previously declared threatened. We develop a two-part model of home damage to analyze the impact of resources in these two situations. We instrument endogenous resources in the damage model based on the resource allocation equations.

We use the AB systems estimator to estimate the set of response resource allocation equations defined in equation (9). The resource allocation equations are interesting in their own right and provide context for the growth and expenditures models. To summarize, we estimate the wildfire growth, expenditures, and damage models independently. The next section describes the AB model used to estimate the resource allocation equation.

3.1.1 Firefighting Resource Allocation Equations

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.[10] In addition, many factors that influence the allocation of response resources

[10] Arellano 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.

are themselves influenced by the use of response resources over the course of the wildfire, which implies that several regressors are likely endogenous.

The AB systems estimator jointly estimates a system of two equations: one in levels, and one in first differences.

$$(11)\quad \bar{y}_{ijt} = \alpha_j \bar{y}_{ij,t-1} + [\mathbf{v}_{it}\ \bar{\bar{\mathbf{y}}}_{-it}]\boldsymbol{\beta}_j + \mathbf{p}_{1ijt}\boldsymbol{\gamma}_j + \mathbf{p}_{2ij}\boldsymbol{\delta}_j + \varepsilon_{ijt} \quad \text{where} \quad \varepsilon_{ijt} = u_{ij} + e_{ijt}$$

$$(12)\quad \Delta\bar{y}_{ijt} = \alpha_j \Delta\bar{y}_{ij,t-1} + \Delta[\mathbf{v}_{it}\ \bar{\bar{\mathbf{y}}}_{-it}]\boldsymbol{\beta}_j + \Delta\mathbf{p}_{1ijt}\boldsymbol{\gamma}_j + \Delta e_{ijt}$$

where $\bar{y}_{ijt}$ is the number of resources of type $j = \{$`Crew 1`, `Crew 2`, `Aircraft`, `Dozers`, and `Engines`$\}$ committed to fire i at time t, $\mathbf{v}_{it}$ is a vector of endogenous covariates, $\bar{\bar{\mathbf{y}}}_{-it}$ is a vector of endogenous resources dispatched to all other fires, $\mathbf{p}_{1ijt}$ is a vector of time-varying control covariates, $\mathbf{p}_{2ij}$ is a vector of time-invariant control covariates, $\alpha_j, \boldsymbol{\beta}_j$, $\boldsymbol{\gamma}_j$, and $\boldsymbol{\delta}_j$ are coefficients for resource j, and Δ is a first-difference operator. Covariates in $\mathbf{v}$ are endogenous and are instrumented by a vector of covariates $\mathbf{z}$ that include l lags of y and covariates in $\mathbf{v}$, $\mathbf{p}_1$, and $\mathbf{p}_2$.

Based on the theoretical model, wildfire managers respond to threatened assets and expected damage. Therefore, the covariates in $\mathbf{v}$ include `Threatened Homes`, a categorical variable `Growth Potential` measured on a four-point scale (low, medium (baseline), high, and extreme), and `Percent Contained`. Resources allocated to all other fires, $\bar{\bar{\mathbf{y}}}$, capture resource constraints. Strictly exogenous time-varying covariates, $\mathbf{p}_1$, include the `Day of Year` (sin and cosine transform), `Count (`I`)` (the number of fires currently burning within the region), and a measure of `Inaccessibility` (low and medium (baseline), high and extreme). Strictly exogenous time-invariant covariates, $\mathbf{p}_2$, are measured at the point of ignition and include the `Palmer Drought Severity Index`, `Cause`, `Elevation`, `Slope`, `Fuel Model`, `Wilderness` designation indicator, `lnMedVal` median home value, `Hdensity20` home density within 20 miles, `lnDistance` distance to nearest Census Designated Place, `Year`, and `Region`.

The AB systems estimator forms two sets of moment conditions: one set for the levels equation, and another set for the equations in differences. Instruments in the levels equation (11) include exogenous covariates, $\mathbf{p}_1$, $\mathbf{p}_2$, and weather conditions (`Temperature`, `Precipitation`, `Wind`, and `Relative Humidity`), as well as first differences of lagged endogenous covariates, $\Delta\mathbf{v}_{t-l}$ for $l > 2$. Instruments in the difference equation (12) include differenced exogenous covariates, $\Delta\mathbf{p}_1$[11] and weather conditions, and levels of lagged endogenous covariates $\mathbf{v}_{t-l}$ for $l > 2$. Use of lag l of endogenous covariates as instruments is valid when the error v_{ijt} is not correlated with $e_{ij,t-l}$ (Roodman, 2006). Arellano and Bond (1991) construct a test of autocorrelation in l lags of first-difference residuals to determine the validity of lags l and greater.[12] While the moment conditions corresponding to equations (11) and (12) can be consistently estimated separately by GMM, joint estimation yields efficiency gains (Roodman, 2006).

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. We use the two-step version of the estimator, which is robust to within-panel heteroskedasticity and autocorrelation (Roodman, 2006).[13] Standard errors of model parameters are estimated based on the two-step estimator correction proposed

[11] Covariates $\mathbf{p}_2$ are time-invariant and not available as instruments in the difference equation.

[12] The 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 $\sum_{it} y_{ij,t-2}\hat{e}_{ijt} = 0$ for each j since the sum of zeros is zero. This method reduces the likelihood of overidentification (Roodman, 2006).

[13] Any 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 $\mathbf{A}_r = (\mathbf{z}'\boldsymbol{\Omega}\mathbf{z})^{-1}$.

by Windmeijer (2005) and are clustered at the fire level.

3.1.2 Wildfire Expenditures and Growth

We estimate the expenditure and growth equations described in equations (10a) and (10b) independently using the AB systems estimator. Daily wildfire growth and expenditures are logged because the empirical distribution of the variables is skewed. The system GMM estimator for daily fire growth is

$$\ln(a)_{it} = \alpha_1 \ln(a)_{i,t-1} + \bar{\mathbf{y}}_{i,t-1}\boldsymbol{\beta} + \mathbf{p}_{1it}\boldsymbol{\gamma} + \mathbf{p}_{2i}\boldsymbol{\delta} + \varepsilon_{it} \quad \text{where} \quad \varepsilon_{it} = u_i + e_{it}$$

$$\Delta \ln(a)_{it} = \alpha_1 \Delta \ln(a)_{i,t-1} + \Delta\bar{\mathbf{y}}_{i,t-1}\boldsymbol{\beta} + \Delta\mathbf{p}_{1it}\boldsymbol{\gamma} + \Delta e_{it}$$

where lagged growth is included to capture natural fire dynamics, $\bar{\mathbf{y}}_{i,t-1}$ are resources dispatched during the previous planning period as specified in equation (10a), $\mathbf{p}_1$ is a vector of exogenous time-varying covariates including `Day of Year`, `Temperature`, `Precipitation`, `Wind`, `Humidity`, and `Inaccessibility`, $\mathbf{p}_2$ is previously defined excluding `lnMedVal`, `Hdensity20`, and `Distance`, which are assumed to influence resource allocation but not fire growth directly.[14]

Similarly, the estimator for daily wildfire expenditure is

$$\ln(c)_{it} = \alpha_1 \ln(a)_{i,t-1} + \bar{\mathbf{y}}_{i,t}\boldsymbol{\beta} + \mathbf{p}_{1it}\boldsymbol{\gamma} + \mathbf{p}_{2i}\boldsymbol{\delta} + \varepsilon_{it} \quad \text{where} \quad \varepsilon_{it} = u_i + e_{it}$$

$$\Delta \ln(c)_{it} = \alpha_1 \Delta \ln(a)_{i,t-1} + \Delta\bar{\mathbf{y}}_{i,t}\boldsymbol{\beta} + \Delta\mathbf{p}_{1it}\boldsymbol{\gamma} + \Delta e_{it}$$

where daily fire growth is again included to capture fire dynamics, $\bar{\mathbf{y}}_{i,t}$ are contemporaneous endogenous resources as specified in equation (10b), $\mathbf{p}_1$ is vector of exogenous

[14] As a robustness check, we estimate a model with endogenous resources, `lnMedVal`, `Hdensity20`, and `Distance`; then, estimate a model without endogenous resources but include `lnMedVal`, `Hdensity20`, and `Distance`. The home and distance variables are statistically significant in the model without endogenous resources but not significant in the model with endogenous resources.

time-varying covariates that includes Day of Year, Inaccessibility, and a Count (I), $\mathbf{p}_2$ is a vector of exogenous time-invariant covariates previously defined. Response resource covariates are instrumented in both models based on the equations described in section 3.1.1. We implement the Arellano-Bond systems estimator with *xtabond2* for Stata 13 (Roodman, 2006).

3.1.3 Homes Damaged

We observe the number of homes damaged and destroyed in each planning period. Conceptually, damage to homes occurs in two steps. Consider a wildfire under active suppression in which no homes are threatened at $t = 0$. At $t = 1$, homes can be either threatened or not depending on fire activity and the proximity of homes. If homes become threatened at $t = 2$, the fire can either damage the threatened homes or not. Assigning suppression resources to protect homes may mitigate the home damage.

We develop a two-part econometric model to estimate damage to homes as a function of endogenous suppression resources. Part one consists of a probit regression of whether homes were threatened at $t = 1$ as a function of suppression resources dispatched at $t = 0$ conditional on no threatened homes at $t = 0$. The objective of this specification is to discern whether resources dispatched while no homes were threatened reduces the probability that any homes become threatened. Part two of the model consists of a probit regression of whether any homes were damaged at $t = 2$ as a function of suppression resources dispatched at $t = 1$ conditional on threatened homes at $t = 1$. This specification compares the impact of resources on the subset of observations with at least one threatened home.

We estimate parts one and two separately because the models are independent by construction of the sample. Part one is conditional on zero threatened homes while part two is conditional on at least one home threatened. The log-likelihood function for part one is

$$\text{(13)} \quad \begin{aligned} \ln L_i =& v_{it}^* \ln \Phi(m_{it}) + (1 - v_{it}^*) \ln(1 - \Phi(m_{it})) - \frac{\rho}{2} \ln 2\pi - \frac{1}{2} \ln |\boldsymbol{\Sigma}_{22}| \\ & - \frac{1}{2}(\bar{\mathbf{y}}_{i,t-1} - [\mathbf{p}_{i,t}\ \mathbf{p}_{i,t-1}]\boldsymbol{\Pi})\boldsymbol{\Sigma}_{22}^{-1}(\bar{\mathbf{y}}_{i,t-1} - [\mathbf{p}_{i,t}\ \mathbf{p}_{i,t-1}]\boldsymbol{\Pi})' \quad \text{if } v_{i,t-1} = 0 \end{aligned}$$

where $m_{it} = (1 - \boldsymbol{\Sigma}_{21}' \boldsymbol{\Sigma}_{22}^{-1} \boldsymbol{\Sigma}_{21})^{\frac{1}{2}}(\mathbf{p}_{i,t}\boldsymbol{\eta} + (\bar{\mathbf{y}}_{i,t-1} - [\mathbf{p}_{i,t}\ \mathbf{p}_{i,t-1}]\boldsymbol{\Pi}))\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21})$, $v_{it}^* = 1$ if $v_{it} > 0$, $\Phi()$ is the standard normal CDF, $\bar{\mathbf{y}}_{i,t-1}$ is a vector of lagged endogenous suppression resources, $\mathbf{p}_{it}$ is a vector of exogenous covariates at time t some of which serve as instruments, $\boldsymbol{\Sigma}$ is the covariance of the `Threatened Homes` disturbance and the IV disturbances, where element Σ_{11} is normalized to one for identification.[15] The covariates `lnMedVal`, `Hdensity20`, `Day of Year`, and `Inaccessibility`$_{t-1}$ are excluded from the `Threatened Homes` equation to identify $\bar{\mathbf{y}}_{i,t-1}$.

The log-likelihood for part two is

(14)

$$\begin{aligned} & \ln L_i = d_{it}^* \ln \Phi(m_{it}) + (1 - d_{it}^*) \ln(1 - \Phi(m_{it})) - \frac{\rho}{2} \ln 2\pi - \frac{1}{2} \ln |\boldsymbol{\Sigma}_{22}| \\ & - \frac{1}{2}(\bar{\mathbf{y}}_{i,t-1} - [\mathbf{p}_{i,t}\ \mathbf{p}_{i,t-1}\ v_{i,t-3}]\boldsymbol{\Pi})\boldsymbol{\Sigma}_{22}^{-1}(\bar{\mathbf{y}}_{i,t-1} - [\mathbf{p}_{i,t}\ \mathbf{p}_{i,t-1}\ v_{i,t-3}]\boldsymbol{\Pi})' \quad \text{if } v_{i,t-1} > 0 \end{aligned}$$

where $m_{it} = (1 - \boldsymbol{\Sigma}_{21}' \boldsymbol{\Sigma}_{22}^{-1} \boldsymbol{\Sigma}_{21})^{\frac{1}{2}}(\mathbf{p}_{i,t}\boldsymbol{\eta} + (\bar{\mathbf{y}}_{i,t-1} - [\mathbf{p}_{i,t}\ \mathbf{p}_{i,t-1}\ v_{i,t-3}]\boldsymbol{\Pi}))\boldsymbol{\Sigma}_{22}^{-1}\boldsymbol{\Sigma}_{21})$. We include the three period lag of threatened homes as an instrument for lagged suppression resources. The choice of this specification is based on difference in Hansen overidentification tests from the estimation of the resource allocation equations. These tests show that the third lag is deep enough to be exogenous to $\bar{\mathbf{y}}_{i,t-1}$.

The two part model is estimated by full information maximum likelihood (FIML) using Stata's *ivprobit* command. We include only `Crew 1` and `Engine` in $\bar{\mathbf{y}}$ because

[15] The Cholesky decomposition of $\boldsymbol{\Sigma}$ is estimated in practice.

the number of parameters increases with each endogenous regressor causing convergence problems. The resource allocation results provide evidence for this specification. We cluster standard errors at the fire level to allow for serial correlation and heteroskedasticity within a fire.[16] Although we observe the counts of threatened and damaged homes, the counts of damaged homes is sparse in the data. We focus on the impact of suppression resources on the extensive margin of threat and damage to homes.

4 Results

The structure of our model assumes that firefighting resources are allocated, and expenditures accrue, in period t while wildfire growth and damage to homes is realized in period $t+1$. We present the empirical results in that order to facilitate interpretation. Table 3 contains selected coefficient estimates and associated standard errors of the covariates in the resource allocation equations where the dependent variable is the number of response resources allocated to fire i. Full regression estimate tables are located in the Supplementary Material. The bottom of the table includes the model χ^2 test, the p-value of the Hansen overidentification test, the lag bounds that define the instrument set, and the total number of instruments used in each equation.[17] Arellano-Bond autocorrelation tests are presented at the bottom of the full results table in the Supplementary Material. All resource allocation equations are based on 2,799 observations on 585 fires.

The lagged dependent variable, $\bar{\mathbf{y}}_{i,t-1}$, the resources dispatched to other fires in the

[16]Alternatively, each part of the model can be estimated as a two-step estimator (Rivers and Vuong, 1988) that does not suffer from the instability of the MLE but also does not cluster standard errors. We present our model with all resources, $\bar{\mathbf{y}}_{i,t-1}$, as a robustness check in located in the Supplementary Material.

[17]The null hypothesis of the Hansen test is that the system of moment conditions is not overidentified.

region, $\bar{\mathbf{y}}_{-i,t}$, `Threatened Homes` (from fire i and fires $-i$), `Growth Potential`, and `Percent Contained` are all considered endogenous and are instrumented by lagged values of the endogenous covariates as well as external covariates. The Arrellano-Bond (AB) test of autocorrelation in first differences guides the depth of lags needed to ensure exogeneity of the instruments.[18] The AB test provides evidence that: lags three and beyond are valid for Type 1 and 2 Crews while lags two and beyond are valid for all other resource equations.

Threatened homes are among the highest priority of both individual fire managers and regional command units. Therefore, we expect that resources trained to protect structures would be assigned to fires that threaten homes. The positive and statistically significant coefficients on `Threatened Homes` in the Crew 1 (0.016) and Engine (0.007) equations indicate that fires with 1000 threatened homes receive 16 additional type 1 firefighters and 7 additional engine crew members (there are generally 5 crew members per engine). Moreover, an increase of threatened homes on other concurrent fires $-i$ leads to fewer type 1 crews dispatched to fire i. In contrast, fires with threatened homes are less likely to receive type 2 crews, aircraft, and dozers. These results reflect the comparative advantage and strategic use of type 1 and engine crews to protect structures. Incident commanders receiving limited suppression resources from the regional command unit would likely apply the type 1 and engine crews to the section of fire perimeter closest to the threatened homes. Indeed, our result provides empirical support for the simulation model in Fried, Gilless, and Spero (2006) in which incident commanders divert resources from containment to home protection during initial attack.

Resource allocation is also influenced by the incident commander's perception of

[18] Intuitively, autocorrelation in the error after the fixed component is differenced out renders lagged endogenous variables invalid instruments. Therefore, the AB test reveals whether chosen instruments are far (lagged) enough from the endogenous regressors.

Table 3: Selected Coefficient Estimates from Resource Allocation Models.

	Crew 1		Crew 2		Aircraft		Dozer		Engine	
	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.
Threatened Homes	0.016*	(0.009)	−0.006	(0.006)	−0.0002***	(0.0001)	−0.0005	(0.001)	0.007*	(0.003)
Threatened Homes$_{-i}$	−0.012*	(0.007)	−0.005	(0.007)	−0.0003***	(0.0001)	−0.0002	(0.001)	0.006	(0.012)
Growth Low	−203.167	(156.697)	31.725	(49.547)	−3.581	(2.541)	−8.799	(8.618)	10.648	(46.146)
Growth High	−65.938	(142.298)	47.468	(52.947)	−3.733	(2.591)	−3.365	(7.977)	68.405	(66.522)
Growth Extreme	−87.880	(87.832)	24.568	(53.647)	1.227	(2.797)	12.707	(10.668)	105.613**	(47.256)
Count (I)	−2.359*	(1.242)	−0.308	(0.757)	−0.005	(0.031)	0.127	(0.137)	−0.756	(0.631)
Type 1 Crews$_{-i}$	−0.004	(0.009)	−0.003	(0.007)	0.000	(0.001)	0.000	(0.002)	0.004	(0.012)
Type 2 Crews$_{-i}$	−0.012	(0.282)	−0.011	(0.213)	−0.003	(0.004)	0.032	(0.037)	0.000	(0.104)
Aircraft$_{-i}$	−14.766	(12.241)	−3.709	(6.602)	−0.020	(0.190)	1.644	(1.503)	5.056	(6.921)
Dozers$_{-i}$	1.790	(5.155)	0.254	(2.741)	−0.129	(0.151)	0.082	(0.466)	0.087	(3.118)
Engines$_{-i}$	−0.513	(0.648)	0.151	(0.364)	−0.001	(0.021)	−0.032	(0.072)	−0.014	(0.460)
Resource$_{t-1}$	0.870***	(0.119)	0.576***	(0.185)	0.806***	(0.104)	0.683***	(0.226)	0.837***	(0.060)
Inaccess High	−1.632	(22.707)	−0.199	(12.333)	0.468	(0.397)	−0.726	(1.819)	−10.382	(11.487)
Inaccess Extreme	−1.140	(18.013)	−6.146	(13.146)	−0.335	(0.517)	−3.955*	(2.262)	−17.532**	(8.913)
PDSI	−1.153	(2.466)	−1.200	(1.556)	0.032	(0.060)	0.560	(0.515)	0.924	(1.960)
Wilderness	−3.682	(16.962)	0.831	(11.800)	−0.219	(0.374)	−0.506	(2.158)	2.834	(12.189)
lnMedValue	10.032	(6.704)	3.884	(2.803)	0.275*	(0.144)	0.596	(0.537)	0.261	(3.027)
lnDistance	−0.163	(0.499)	−0.383	(0.351)	0.009	(0.015)	0.077	(0.080)	0.096	(0.359)
χ^2 Statistic	4184		1692		4540		1235		10420	
Hansen Test P-val	0.669		0.455		0.409		0.511		0.471	
Instrument Lag Depth	(3 : 4)		(3 : 4)		(2 : 4)		(2 : 5)		(2 : 5)	
Number of Instruments	61		59		68		76		76	

Fires=585, Observations=2,799

legend: * p< 0.1; ** p< 0.05; *** p< 0.01

Omitted coefficients: Percent Contained, Day of Year, Lightning, Elevation, Slope, Fuel Model, Hdensity20, Year, Region a wildfire's growth potential. Extreme growth potential increases the allocation of all resources except type 1 crews (although only statistically significant in the Engine model). We find little evidence that more suppression resources are dispatched to fires during low growth periods as suggested by Finney, Grenfell, and McHugh (2009). The coefficients on `Growth Potential Low` in the Crew 2 (31.725) and Engine (10.648) models are positive but not statistically significant. However, our result is consistent with our theoretical model in which fire with low expected growth have a marginal benefit or shadow value lower than another fire in the region with higher expected growth.

The coefficient estimates on Resource$_{-i}$ provides information on the opportunity cost and substitutability of resources. We would expect that when resources are limited, more resources assigned to fires $-i$ increases the opportunity cost of resources assigned to fire i. The coefficients on `Count` (I) are negative in all models except Dozers indicating that more fires within a jurisdiction increase the likelihood that resource constraints bind at the regional level, $\bar{\bar{\mathbf{y}}}$. We find additional evidence for the impact of resource constraints on the dispatch to fire i. While not statistically significant, the coefficients on resources $\bar{\mathbf{y}}_{-i}$ are negative in Crew 1, Crew 2, and Aircraft models indicating that more resources dispatched to other fire reduce the dispatch to fire i. We find less impact of the resource constraints on the dispatch of Dozers and Engines.

We find strong evidence of wildfire dynamics and reallocation frictions. Frictions may include logistic and mobility factors such as transport of dozers, but may also reflect political influence in certain regions. The lagged dependent variable also captures the fact that a crown fire is rarely suppressed in a single day. The lagged dependent in each model is statistically significant and ranges from 0.57 (Crew 2) to 0.87 (Crew 1). These results suggest that type 1 crews, aircraft, and engines are more likely than type 2 crews and dozers to remain on their assigned fires over time. This high persistence of type 1 firefighter captures the fact that these autonomous and skilled units are often assigned to a fire from discovery until control is imminent.

Other environmental and economic factors influence suppression resource allocation. Inaccessibility limits the dispatch of resources. Fires that are extremely inaccessible receive 3.955 fewer Dozer crew members (and 1-2 associated dozers) and 17.532 fewer Engine crew members (3-4 associated engines). Counties with higher median home value (`lnMedValue`) receive more resources. This result could reflect subjective values of incident commanders and regional command, but could also be due to the impact of property values on tax revenue and expenditure on local resources.

4.1 Wildfire Expenditures, Growth, and Damage

Table 4 contains the results of the semi-log regressions of wildfire growth, expenditures, and home damage on suppression resources. The timing of the resource allocation decisions described in the theory implies that contemporaneous resources appear in the expenditure equation while lagged resources appear in the wildfire growth and damage equations. The model χ^2 statistic is based on a Wald test that all estimates are jointly zero. The exogeneity test in the Growth and Expenditure (AB) models is the Hansen overidentification test, for which the null hypothesis is the moment conditions are zero. The exogeneity test in the two-part IV probit model is a Wald test where the null hypothesis is that elements of the covariance matrix, $\boldsymbol{\Sigma}$, are jointly zero i.e., equations are independent. We reject the null that type 1 and engines crews are exogenous, which supports the IV specification. The number of instruments indicates the covariates excluded from the main regression in the two-part model; all exogenous covariates also serve as instruments for the endogenous suppression resources. The number of observations and fires varies across wildfire outcomes because of missing observations, and because the two-part damage model is conditional on a subset of observations.

Our results suggest that suppression resources have little impact on daily fire growth, but do mitigate damage to threatened homes and increase daily expenditure. On average, each additional type 2 crew member increases daily expenditure by 0.58% (point estimate of 0.006), while each additional aircraft personnel increases daily expenditure by 35%.[19] Type 1 and engines crews are generally assigned to protect homes when threatened. Conditional on zero threatened homes yesterday, neither type 1 crews nor engines dispatched yesterday have a statistically significant impact on the probability that homes become threatened today. If however, homes are threatened yesterday, one additional type 1 crews dispatched yesterday reduce the probability that at least one home is damaged today (ME of -0.0004/type 1 firefighter calculated at means).[20]

Lagged growth covariates are included in the Wildfire Growth and Expenditure models to capture the physical dynamics of the fire. These coefficients can be interpreted directly as elasticities. The coefficient on `lnArea` in the Expenditure equation is 0.383, which implies that a 1% increase in fire growth leads to an increase in expenditures of 0.38% ceteris peribus. This result suggests that expeditures do not scale linearly with fire growth. The coefficient on $\texttt{lnArea}_{t-1}$ is 0.78 in the Growth equation, indicating that unconditional fire growth today is highly correlated with yesterday's fire growth due to spatiotemporal correlation in environmental conditions

[19]Marginal effects (ME) in the semilog models are calculated by $f^c(\beta) = [\exp(\beta) - 1] * 100$ for continuous covariates and $f^d(\beta) = [\exp(\beta - 0.5V(\beta)) - 1] * 100$ for dummy variables (Kennedy, 1981). Marginal effects in the IV probit models are $\partial\Phi(\mathbf{x}\hat{\boldsymbol{\beta}})/\partial x_j = \hat{\beta}_j \Phi(\mathbf{x}\hat{\boldsymbol{\beta}})$.

[20]We find no evidence that type 2 crews, aircraft, or dozers reduce damage to households based on the two-step estimator (results in Supplementary Material). However, the power of the two-step estimator relative to the preferred FIML is low.

Table 4: Selected Coefficient Estimates of Wildfire Growth and Expenditure Models and Two-part Model of Threatened and Damaged Homes

	Daily Growth		Daily Expenditure		Daily Threatened and Damaged Homes Pr(Thr | Thr_{t-1}=0)		Daily Threatened and Damaged Homes Pr(Dam | Thr_{t-1}=1)	
	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.
`lnArea`$_{t-1}$	0.782***	(0.066)	0.383***	(0.118)	–		–	
`Crew 1`[a]	0.000	(0.001)	0.001	(0.003)	0.004	(0.003)	−0.004*	(0.002)
`Crew 2`[a]	−0.002	(0.001)	0.006*	(0.003)	–		–	
`Aircraft`[a]	0.038	(0.032)	0.302***	(0.101)	–		–	
`Dozers`[a]	0.004	(0.006)	−0.013	(0.024)	–		–	
`Engines`[a]	−0.001	(0.001)	−0.002	(0.002)	0.001	(0.004)	0.003***	(0.001)
`Count` (I)	–		0.184***	(0.051)	–		–	
`lnMedValue`	–		0.773***	(0.059)	–		–	
`lnDistance`	–		−0.022***	(0.007)	–		–	
`Hdensity20`	–		−0.001**	(0.000)	–		–	
`Temperature (F)`	0.018***	(0.004)	–		0.009*	(0.005)	−0.014*	(0.008)
`Precipitation (in)`	−0.908	(1.314)	–		−0.662	(0.637)	−0.815	(0.839)
`Wind (mph)`	0.023***	(0.006)	–		0.013**	(0.005)	0.015*	(0.009)
`Humidity (%)`	−0.011***	(0.002)	–		−0.002	(0.003)	−0.001	(0.006)
`Lightning`	0.266***	(0.084)	−0.772***	(0.184)	0.131	(0.181)	−0.130	(0.258)
`Grass`	−0.185**	(0.092)	−0.312*	(0.188)	−0.060	(0.100)	0.159	(0.253)
`Brush`	−0.175	(0.115)	−0.544**	(0.229)	−0.003	(0.114)	0.579	(0.381)
`Wilderness`	−0.035	(0.084)	−1.338***	(0.219)	−0.112	(0.185)	−0.234	(0.307)
`PSW Region (CA)`	0.082	(0.192)	−1.069***	(0.405)	−0.405*	(0.212)	0.854*	(0.477)
χ^2 Statistic	68,514		62,855		30		101	
Exogeneity Test P-val[b]	0.585		0.331		0.396		0.054	
Instrument Lag Depth	(3 : 5)		(8 : 12)					
Number of Instruments[c]	69		74		6		8	
Number of Observations	3,076		3,865		3,898		2,508	
Number of Fires	612		864		658		307	

legend: * $p< 0.1$; ** $p< 0.05$; *** $p< 0.01$

Omitted coefficients: `Day of Year`, `Elevation`, `Slope`, `Fuel Model`, `Year`, `Region`

[a] denotes lagged in the Growth and Damage models

[b] Hansen overidentification test in AB models and χ^2 test of endogeneity in IV probit model

[c] Count of exclusion restrictions in Damage models

and heat from the prior day. Including lagged wildfire growth helps to control for inherent wildfire dynamics and isolate the marginal effects of suppression resources on wildfire outcomes. The two-part damage model does not include endogenous lagged fire growth because the IV probit model would not converge.

The control variables reveal that despite management efforts, environmental and economic conditions still have a statistically significant impact on wildfire growth and expenditure. Weather covariates are generally consistent with expectation and nearly all statistically significant in the wildfire growth equation. A one degree increase in `Temperature` increases growth by 1.8% while a one mile per hour increase in `Wind` increases growth by 2.31%. On the other hand, a 1% increase in relative humidity decreases growth by 1.1%. Weather is assumed to influence wildfire expenditures through suppression resources and fire growth. Weather covariates are instruments in the Expenditure model but do not enter directly. However, weather covariates are included in the two-part damage model to partially capture the influence of wildfire growth.

Economic conditions have statistically significant impacts on wildfire expenditures. Our results suggest that an additional fire within the regional command jurisdiction, `Count` (I), increases expenditures by over 20% per day. While the suppression resource scarcity effect should be captured by endogenous resources, `Count` (I) may also capture additional expenditures or charges such as overtime. The median home value expenditure elasticity is 0.773 (`lnMedVal`), which may capture variation in rental rates and wages across the Western states. We find that an additional 10 homes per square mile (within 20 miles) of the ignition point reduces expenditure by 1.1%. This result suggests that more densely populated area reduce expenditure, which may be capturing dynamic effects of more aggressive strategies in more densely populated areas.

5 Discussion

Our results suggest that type 1 crews and engines are more likely to be dispatched to fires with threatened homes, and that at least type 1 crews mitigate the probability that a home is damaged or destroyed. This result has important policy implications. It is conceivable that the incentive to protect homes diverts resources from other management objectives that may include protection of other (possibly public) assets such as watersheds or endangered species habitat. In this paper, we focus on a very important private asset, houses. An expansion of our empirical model to include other threatened assets would permit an investigation of the trade offs that wildfire managers make when faced with decisions between two assets. In principle, their decisions could reveal the relative value of assets. Of particular interest might be the decisions made to protect either private or public assets.

The results support two important features of our theoretical model. First, resource allocation is influenced by the incentive to protect threatened assets, and particularly, residential property. Second, the resources dispatched to achieve protection objectives do mitigate the risk of damage. Surprisingly, we find little evidence that type 1 and engine crews used to protect threatened homes dramatically influence short term wildfire expenditures. One explanation for this result could be due to the versatility and full-time status of type 1 crew members. If type 1 crew firefighters are on duty during a suppression effort, they are probably assigned to a fire. The cost of employing the firefighter accrues to that fire whether they are activity engaged in home protection or other activities. Further information on each resources assignment during their deployment could help identify the impact of activities performed by resources on wildfire expenditures.

Our theoretical model of optimal resource allocation simplifies the analytics by assuming perfect coordination and information between a set of individual fire managers and a regional command unit. While information is far from perfect during an emergency response and expectations may differ between individual fire managers and the regional command unit, the model provides an analytical framework to understand the complex coordination of resource allocation under optimal conditions. In reality, though, individual fire managers may benefit by overstating the marginal benefit of a resource in an incomplete information framework. However, if all individual fire managers face the same incentive to overstate their marginal benefit, the result would be "inflated" shadow prices with no impact on the allocation of resources. Further research could build on this model by relaxing the assumption of perfect information.

Although the empirical results provide a number of important and intuitively plausible results, the relatively weak statistical significance of many coefficient estimates highlights the critical need for high quality data on resource allocation and wildfire outcomes. Understanding suppression effectiveness and optimal resource allocation require complex data-intensive models that along with better data can translate into more accurate models. Model accuracy would benefit policy-makers as well as fire managers who increasingly rely on decision support systems to develop management strategies. Given that more than $2 billion is spent by the federal government each year on wildfire management, improved data collection efforts by firefighting agencies are likely to be an effective investment in the effort to reduce wildfire losses and suppression expenditures.

The use of aircraft to manage wildfire is a contentious issue. Incident commanders recognize the limitations of aircraft during a well-established fire, but often face political pressure to use the resource (Donovan, Prestemon, and Gebert, 2011). Firefighting aircraft are now perceived by the public as the symbol of a fully mobilized response and provide a sense of comfort when communities are threatened by wildfire.

Our results suggest that aircraft are not systematically allocated to fires with more threatened homes. We find that once a fire is beyond initial attack, aircraft (mostly helicopters) do little to mitigate the growth of fire, but increase daily expenditures by over 35% per aircraft unit (Table 4). Moreover, we find no evidence that aircraft mitigate damage to threatened homes. These results contrast with the findings Holmes, Huggett, and Westerling (2008) who find that the use of tankers reduce fire size using single-observation data on fires. While our measure of aircraft consists largely of helicopters, the contrasting results highlight the importance of dynamic allocation decisions throughout the fire.

The daily intervals over which resource allocation and wildfire outcomes are measured is both a strength and weakness of this analysis. We use the high temporal resolution to identify the causal effect of environmental and economic conditions on suppression resource allocation. However, this high resolution may also obscure the impact of the suppression resources on wildfire outcomes. Even though we focus on fires managed under full suppression, strategies may take more than a day to mitigate growth. Incident commanders often plan strategies based on geographic and man-made features as well as expected wildfire behavior. Our model is designed to capture very short term fluctuations in suppression resource dispatch and wildfire outcomes, and may be unable to capture the growth mitigating impact of suppression resources used on strategies implemented over a longer period. Similarly, the threatened homes measure is a subjective measure determined by the incident commander. We are unable to distinguish between threat levels or imminence of the threat to the home. We treat this as a measurement error problem that we address through instrumenting threatened resources in the resource allocation equations. However, the additional noise is likely impacting the efficiency of our coefficient estimates on threatened homes in the resource allocation equations (Table 3).

The rising size and expenditure of wildfire in the US shows no sign of slowing. Indeed, climate change is expected to exacerbate the problem in the coming decades. Despite the extensive literature on wildfire expenditure, few studies have utilized daily data to study the resource allocation decisions and their subsequent impact on wildfire expenditure and growth. Moreover, no studies have used daily data on suppression resource used throughout the management effort to investigate the complex incentives of wildfire managers and the impacts of their decisions on wildfire outcomes. Evaluating the mechanisms by which wildfire and environmental policy impacts outcomes is difficult without understanding resource allocation during a management effort.

References

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.

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.

Blundell, Richard and Stephen Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models". *Journal of Econometrics*, 87(1): pp. 115–143.

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.

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.

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., Jeffrey P. Prestemon, and Krista Gebert. 2011. "The Effect of Newspaper Coverage and Political Pressure on Wildfire Suppression Costs". *Society & Natural Resources*, 24(8): pp. 785–798. DOI: 10.1080/08941921003649482.

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.

FAMWEB. 2012. "National Fire and Aviation Management Web Applications: SIT Reports". Accessed in July, 2012 at https://fam.nwcg.gov/fam-web/.

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.

FIRESCOPE. 2012. "ICS RESOURCES LISTING". Accessed in March, 2013 at http://www.firescope.org.

Fried, J.S., J.K. Gilless, and J. Spero. 2006. "Analysing Initial Attack on Wildland Fires using Stochastic Simulation". *International Journal of Wildland Fire*, 15(1): pp. 137–146.

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 Econonomics of Forest Disturbances*. Ed. by Jeffrey P. Prestemon Thomas P. Holmes and Karen L. Abt. Forestry Sciences. Springer. Chap. 15, pp. 295–322.

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.

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.

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 E. 1981. "Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations". *American Economic Review*, 71(4):

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.

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.E. et al. 2007. "Evaluating Alternative Prescribed Burning Policies to Reduce Net Economic Damages from Wildfire". *American Journal of Agricultural Economics*, 89(1): pp. 63–77.

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.

— 2014. "United State Suppression Cost Statistics". National Interagency Fire Center. Accessed in March, 2014 at http://www.nifc.gov/fireInfo/fireInfo_statistics.html.

NOAA, NCDC. 2014. *The National Oceanic and Atmospheric Administration National Climatic Data Center*. URL: http://www.ncdc.noaa.gov/ (visited on 05/05/2014).

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.

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 and Geoffrey H Donovan. 2008. "Forecasting Resource-Allocation Decisions Under Climate Uncertainty: Fire Suppression with Assessment of Net Benefits of Research". *American Journal of Agricultural Economics*, 90(4): pp. 1118–1129.

Rivers, Douglas and Quang H Vuong. 1988. "Limited information estimators and exogeneity tests for simultaneous probit models". *Journal of Econometrics*, 39(3): pp. 347–366.

Roodman, David. 2006. *How to do xtabond2: An Introduction to Difference and System GMM in Stata*. Working Paper 103. Center for Global Development.

Sparhawk, W. N. 1925. "Use of liability ratings in forest protection". *Journal of Journal of Agricultural Research*, 30, pp. 693–792.

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.

United States Census Bureau. 2011. *2010 Census Summary File 1 United States*.

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.

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.

Supplementary Material

1 Dataset Merging Algorithm

The ICS-209 and NIFMID are datasets managed by two different organizations that do not use a common identifier. Therefore, we develop an algorithm to merge the two datasets based on variables common to both datasets. We 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 $i = 1, ..., n$ denote observations in the ICS-209 dataset and $j = 1, , J$ denote observations from the NIFMID dataset. Calculate the following variables between an observation i and all fires $j = 1, , J$: number of word matches, euclidean distance (based on latitude and longitude), difference in start date, % difference in expenditures, 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 a 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. We 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 expenditures is the absolute value of the difference in the final suppression expenditures reported in the ICS-209 and NIFMID data divided by the maximum of the expenditures figures reported in each dataset.
    - The percent difference in the area is calculated analogously to the percent difference in expenditures

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.

2 Response Resource Conditions on Fires $-i$

We 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, we search back 48 hours for fires burning within the region. We collect data on fires $-i$ for variables $j = \{$Type 1 Crew, Type 2 Crew, Helicopter, Dozer, Engine, Forecasted Temperature, Forecasted Windspeed, Forecasted Humidity,l 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, we 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.

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

  where $x_{z_i ij}$ 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.

3 Full Regression Tables

Table 1: Coefficient Estimates from Resource Allocation Models

	Crew 1		Crew 2		Aircraft		Dozer		Engine	
	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.
$\texttt{Resource}_{t-1}$	0.870***	(0.119)	0.576***	(0.185)	0.806***	(0.104)	0.683***	(0.226)	0.837***	(0.060)
$\texttt{Crew 1}_{-i}$	−0.004	(0.009)	−0.003	(0.007)	0.000	(0.001)	0.000	(0.002)	0.004	(0.012)
$\texttt{Crew 2}_{-i}$	−0.012	(0.282)	−0.011	(0.213)	−0.003	(0.004)	0.032	(0.037)	0.000	(0.104)
$\texttt{Aircraft}_{-i}$	−14.766	(12.241)	−3.709	(6.602)	−0.020	(0.190)	1.644	(1.503)	5.056	(6.921)
$\texttt{Dozers}_{-i}$	1.790	(5.155)	0.254	(2.741)	−0.129	(0.151)	0.082	(0.466)	0.087	(3.118)
$\texttt{Engines}_{-i}$	−0.513	(0.648)	0.151	(0.364)	−0.001	(0.021)	−0.032	(0.072)	−0.014	(0.460)
Threatened Homes	0.016*	(0.009)	−0.006	(0.006)	−0.0002***	(0.000)	0.000	(0.001)	0.007*	(0.003)
$\texttt{Threatened Homes}_{-i}$	−0.012*	(0.007)	−0.005	(0.007)	−0.0003***	(0.000)	0.000	(0.001)	0.006	(0.012)
Growth Low	−203.167	(156.697)	31.725	(49.547)	−3.581	(2.541)	−8.799	(8.618)	10.648	(46.146)
Growth High	−65.938	(142.298)	47.468	(52.947)	−3.733	(2.591)	−3.365	(7.977)	68.405	(66.522)
Growth Extreme	−87.880	(87.832)	24.568	(53.647)	1.227	(2.797)	12.707	(10.668)	105.613**	(47.256)
Percent Contained	−0.093	(0.605)	−0.034	(0.388)	0.004	(0.012)	0.043	(0.105)	0.169	(0.349)
Day of Year (sin)	−4.485	(19.342)	−5.093	(9.306)	0.278	(0.411)	1.355	(2.082)	−4.721	(9.152)
Day of Year (cos)	−0.999	(20.166)	−13.643	(12.217)	0.006	(0.408)	2.562	(2.462)	2.469	(13.952)
Count (I)	−2.359*	(1.242)	−0.308	(0.757)	−0.005	(0.031)	0.127	(0.137)	−0.756	(0.631)
Inaccess High	−1.632	(22.707)	−0.199	(12.333)	0.468	(0.397)	−0.726	(1.819)	−10.382	(11.487)
Inaccess Extreme	−1.140	(18.013)	−6.146	(13.146)	−0.335	(0.517)	−3.955*	(2.262)	−17.532**	(8.913)
PDSI	−1.153	(2.466)	−1.200	(1.556)	0.032	(0.060)	0.560	(0.515)	0.924	(1.960)
Lightning	0.009	(21.868)	−5.520	(11.577)	0.266	(0.446)	1.378	(1.601)	−10.786	(7.885)
Elevation	−0.003	(0.003)	−0.002	(0.002)	0.000	(0.000)	0.000	(0.001)	−0.001	(0.002)
Slope	−0.238	(0.317)	−0.125	(0.195)	0.011	(0.009)	0.018	(0.040)	−0.052	(0.148)
Grass	19.271	(16.595)	2.990	(8.566)	−0.284	(0.337)	0.173	(1.700)	10.213	(10.080)
Brush	9.753	(15.520)	9.627	(10.946)	0.947*	(0.519)	4.108	(3.230)	12.209	(8.859)
Slash	14.052	(16.484)	−0.639	(16.875)	0.295	(0.336)	1.679	(2.353)	−0.726	(10.523)
Wilderness	−3.682	(16.962)	0.831	(11.800)	−0.219	(0.374)	−0.506	(2.158)	2.834	(12.189)
lnMedValue	10.032	(6.704)	3.884	(2.803)	0.275*	(0.144)	0.596	(0.537)	0.261	(3.027)
Hdensity20	−0.001	(0.036)	0.008	(0.022)	0.000	(0.001)	0.001	(0.005)	−0.023	(0.027)
lnDistance	−0.163	(0.499)	−0.383	(0.351)	0.009	(0.015)	0.077	(0.080)	0.096	(0.359)

continued

continued.

	Crew 1		Crew 2		Aircraft		Dozer		Engine	
	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.
`2004`	13.323	(19.313)	−14.069	(13.244)	−0.243	(0.541)	−1.514	(2.415)	1.948	(14.159)
`2005`	4.490	(27.786)	−11.255	(14.165)	−0.594	(0.672)	-6.637^{*}	(3.824)	−2.296	(15.988)
`2006`	−8.881	(15.192)	−23.289	(16.136)	-0.809^{**}	(0.382)	-4.364^{**}	(2.204)	−2.855	(10.503)
`2007`	−18.909	(19.181)	−17.896	(18.706)	−0.459	(0.403)	−1.159	(1.897)	2.322	(9.287)
`2008`	6.382	(29.114)	−18.957	(16.076)	0.296	(0.725)	0.953	(2.617)	−5.637	(11.484)
`2009`	−22.425	(33.739)	3.667	(22.767)	−1.004	(0.623)	−2.006	(3.376)	0.340	(15.821)
`2010`	−13.352	(29.023)	−6.824	(19.351)	−0.015	(0.669)	−2.254	(3.014)	13.483	(14.299)
`North`	11.252	(26.211)	−20.052	(21.737)	−0.772	(0.566)	−0.640	(3.022)	−8.226	(11.619)
`Southwest`	18.602	(47.936)	−20.892	(24.174)	−1.163	(0.754)	−1.530	(4.103)	3.327	(12.598)
`Intermountain`	9.300	(47.913)	−7.707	(23.594)	−1.276	(0.901)	−4.459	(5.121)	−16.898	(16.519)
`California`	46.923	(39.596)	−23.576	(22.040)	−0.397	(0.730)	2.536	(2.991)	6.521	(16.238)
`Rocky Mountain`	19.044	(30.164)	−13.328	(20.799)	−0.540	(0.600)	−1.019	(3.782)	−6.912	(15.759)
Pvalue Lag 1	0.097		0.174		< 0.001		0.200		< 0.001	
Pvalue Lag 2	0.258		0.097		0.962		0.446		0.966	
Pvalue Lag 3	0.264		0.563		0.366		0.511		0.953	
Pvalue Lag 4	0.439		0.444		0.421		0.617		0.748	
Pvalue Lag 5	0.144		0.165		0.413		0.878		0.796	
Pvalue Lag 6	0.292		0.857		0.192		0.657		0.543	
Pvalue Lag 7	0.231		0.976		0.273		0.533		0.708	

Lags $\tau == 1, \ldots, 7$ are a valid instruments if they are uncorrelated with $\bar{y}_t$

Table 2: Coefficient Estimates of Wildfire Growth and Expenditure Models and Two-part Model of Threatened and Damaged Homes

	Daily Growth		Daily Expenditure		Daily Threatened and Damaged Homes Pr(Thr | Thr_{t-1}=0)		Pr(Dam | Thr_{t-1}=1)	
	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.
$\ln Area_{t-1}$	0.782***	(0.066)	0.383***	(0.118)	–		–	
Crew 1[a]	0.000	(0.001)	0.001	(0.003)	0.004	(0.003)	−0.004*	(0.002)
Crew 2[a]	−0.002	(0.001)	0.006*	(0.003)	–		–	
Aircraft[a]	0.038	(0.032)	0.302***	(0.101)	–		–	
Dozers[a]	0.004	(0.006)	−0.013	(0.024)	–		–	
Engines[a]	−0.001	(0.001)	−0.002	(0.002)	0.001	(0.004)	0.003***	(0.001)
Day of Year (cos)	0.139	(0.129)	0.024	(0.222)	–		–	
Day of Year (sin)	0.015	(0.101)	0.831***	(0.253)	–		–	
Temperature (F)	0.018***	(0.004)	–		0.009*	(0.005)	−0.014*	(0.008)
Precipitation (in)	−0.908	(1.314)	–		−0.662	(0.637)	−0.815	(0.839)
Wind (mph)	0.023***	(0.006)	–		0.013**	(0.005)	0.015*	(0.009)
Humidity (%)	−0.011***	(0.002)	–		−0.002	(0.003)	−0.001	(0.006)
Inaccessibility High	0.196*	(0.106)	0.239	(0.168)	–		–	
Inaccessibility Extreme	0.120	(0.119)	0.433**	(0.198)	–		–	
Count (I)	–		0.184***	(0.051)	–		–	
Palmer Drought Index	0.015	(0.015)	−0.017	(0.034)	–		–	
Lightning	0.266***	(0.084)	−0.772***	(0.184)	0.131	(0.181)	−0.130	(0.258)
Elevation	0.000	(0.000)	0.000	(0.000)	–		–	
Slope	0.000	(0.001)	0.001	(0.003)	–		–	
Grass	−0.185**	(0.092)	−0.312*	(0.188)	−0.060	(0.100)	0.159	(0.253)
Brush	−0.175	(0.115)	−0.544**	(0.229)	−0.003	(0.114)	0.579	(0.381)
Slash	0.295**	(0.116)	−0.438**	(0.221)	–		–	
Wilderness	−0.035	(0.084)	−1.338***	(0.219)	−0.112	(0.185)	−0.234	(0.307)
lnMedValue	–		0.773***	(0.059)	–		–	
lnDistance	–		−0.022***	(0.007)	–		–	
Hdensity20	–		−0.001**	(0.000)	–		–	

continued

continued.

	Daily Growth		Daily Expenditure		Daily Threatened and Damaged Homes Pr(Thr | Thr$_{t-1}$=0)		Daily Threatened and Damaged Homes Pr(Dam | Thr$_{t-1}$=1)	
	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.	$\boldsymbol{\beta}_t$	S.E.
2004	−0.198	(0.150)	0.117	(0.254)	–		–	
2005	−0.322**	(0.134)	0.270	(0.283)	–		–	
2006	−0.136	(0.093)	−0.273	(0.266)	–		–	
2007	−0.017	(0.094)	−0.373*	(0.220)	–		–	
2008	−0.188*	(0.109)	−0.201	(0.293)	–		–	
2009	−0.225*	(0.133)	0.098	(0.231)	–		–	
2010	−0.514***	(0.179)	−0.240	(0.338)	–		–	
FS Region N	−0.107	(0.115)	−1.177***	(0.390)	–		–	
Southwest	−0.348**	(0.173)	−1.409***	(0.364)	–		–	
Intermountain	−0.172	(0.146)	−1.147***	(0.326)	–		–	
PSW Region (CA)	0.082	(0.192)	−1.069***	(0.405)	−0.405*	(0.212)	0.854*	(0.477)
Rocky Mountain	0.050	(0.182)	−0.097	(0.398)	–		–	
Constant	–		–		−2.739***	(0.522)	−1.054	(1.153)

4 Resource

Table 3: Coefficient Estimates for Model of Persons per Resource

	Coef.	S.E.	Pvalue
Type 1 Crew (Single Resource)	16.573	2.795	< 0.0001
Type 1 Crew (Strike Team)	29.706	3.168	< 0.0001
Type 2 Crew (Single Resource)	12.568	2.371	< 0.0001
Type 2 Crew (Strike Team)	2.645	2.613	0.311
Aircraft	7.041	1.798	< 0.0001
Engine (Single Resource)	4.373	0.603	< 0.0001
Engine (Strike Team)	18.339	1.588	< 0.0001
Dozer (Single Resource)	3.084	0.951	0.001
Dozer (Strike Team)	1.731	1.316	0.189
Constant	7.071	4.171	0.090

N=18,278, Adjusted R^2=0.92

5 Robustness Check

Table 4: Two-step IV Coefficient Estimates of Damage with All Endogenous Resources

	Coef.	S.E.	Pvalue
Crew 1_{t-1}	-0.023	0.020	0.250
Crew 2_{t-1}	-0.012	0.018	0.511
Aircraft_{t-1}	0.729	0.749	0.330
Dozers_{t-1}	-0.038	0.061	0.532
Engines_{t-1}	0.012	0.010	0.237
Temperature (F)	-0.001	0.015	0.959
Precipitation (in)	-1.841	2.436	0.450
Wind (mph)	0.008	0.023	0.714
Humidity (%)	0.010	0.010	0.321
Lightning	-0.066	0.394	0.867
lnMedValue	-0.757	0.970	0.435
Hdensity20	0.000	0.001	0.727
Day of Year (cos)	0.422	0.928	0.649
Day of Year (sin)	1.396	0.645	0.030
Grass	-0.921	0.945	0.330
Brush	-0.654	1.197	0.585
Wilderness	-1.384	1.091	0.204
PSW Region (CA)	1.809	1.516	0.233
Constant	6.335	11.658	0.587

N=2,508, Exogeneity test pval=0.05