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The Role of Previous Fires in the Management and Expenditures of Subsequent Large Wildfires

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Abstract: Previously burned areas can influence the occurrence, extent, and severity of subsequent wildfires, which may influence expenditures on large fires. We develop a conceptual model of how interactions of fires with previously burned areas may influence fire management, fire behavior, expenditures, and test hypotheses using regression models of wildfire size and suppression expenditures. Using a sample of 722 large fires from the western United States, we observe whether a fire interacted with a previous fire, the percent area of fires burned by previous fires, and the percent perimeter overlap with previous fires. Fires that interact with previous fires are likely to be larger and have lower total expenditures on average. Conditional on a fire encountering a previous fire, a greater extent of interaction with previous fires is associated with reduced fire size but higher expenditures, although the expenditure effect is small and imprecisely estimated. Subsequent analysis suggests that fires that interact with previous fires may be systematically different from other fires along several dimensions. We do not find evidence that interactions with previous fires reduce suppression expenditures for subsequent fires. Results suggest that previous fires may allow suppression opportunities that otherwise might not exist, possibly reducing fire size but increasing total expenditures.

Keywords: Suppression expenditures; wildland fire; fire interactions; suppression effort

1. Introduction

Previously burned areas can influence the occurrence, extent, and severity of subsequent wildfires [1–10]. These previously burned areas can also influence the effectiveness of subsequent wildfire containment activities [11–14]. Given a growing need for more ecologically-appropriate fire across the western United States, accurately characterizing the nature of these interactions with previous fires is increasingly important for informing long-term land and fire management strategies [15–20].

Here, we focus on one aspect of this complex problem, namely the degree to which past fires may affect the management of subsequent wildfires. We are interested in understanding whether and how past fires may influence large fire suppression expenditures. In this paper, such suppression expenditures are defined as the costs associated with management decisions to deploy fire suppression resources (e.g., personnel and equipment) to an incident. Although by no means the only variable of interest (e.g., impacts to public health, homes, and wildlife habitat), addressing suppression expenditures is salient for a number of reasons. In the context of the United State Department of

Agriculture (USDA) Forest Service, these reasons include eroded funding for mission-critical non-fire programs due to the escalation of fire program costs [21], critiques from oversight agencies and review boards regarding the agency's inability to quantify the value of investment in suppression [22,23], and recent legislative action to provide a "fire funding fix" by creating a new budget authority for suppression funds [24]. Although many studies have examined factors influencing suppression costs [25–32], the knowledge base regarding the impacts of past fires on the expenditures of subsequent wildfires is far more limited.

A primary step here is to develop a conceptual model and test hypotheses about how interactions with previous fires may affect expenditures. We borrow from [33], who described causal pathways linking fuel treatment inputs to suppression cost outcomes. Indeed, as many fuel treatments are designed to be a surrogate for wildfire—and perhaps most effective when fire is intentionally applied—there is much that could be learned from studies examining relationships between fuel treatments and suppression costs [34,35]. Simulation-based studies suggest that fire-treatment interactions can lead to a reduction in suppression costs due to reductions in fire size, burn severity, or changes in ecological state that correlate to changes in size and severity [36–40]. Perhaps most relevant, [41] used simulation to estimate the expected present value of suppression cost reductions for subsequent fires arising from the fuel treatment effects of a current fire.

Economic theory suggests that the effects on expenditures of interactions with previous fires could be positive or negative. For example, fuel treatments may increase the marginal productivity of suppression resources, such that managers may opt to invest in greater suppression effort [42]. Recent empirical research in fact supports this assertion, finding a positive association with fire management costs on days when a fire encounters a previously burned or treated area [43]. Further, strategic choices about increasing (decreasing) daily effort/cost can be offset by shorter (longer) overall fire durations [44].

To test our hypotheses regarding possible pathways through which previous fires may affect subsequent fire management decisions and expenditures we leverage a recently developed regression model of suppression expenditures that incorporates spatially and temporally descriptive data [29]. We geospatially overlay past large fire perimeters (greater than 400 hectares) obtained from the Monitoring Trends in Burn Severity (MTBS) project [45], and directly calculate area pre-burned and perimeter overlap with fires in the expenditure data. We then examine relationships between indicators of previous fire interactions (binary interaction with a previous fire, percent area pre-burned by time since fire, and percent perimeter overlap) and suppression expenditures. We also explore relationships between fire interactions and fire size to help understand potential pathways for previous fires to affect suppression expenditures. In subsequent sections we describe a conceptual model of previous fire effects on suppression expenditures and our data analysis and modeling approach, present statistical results and key findings, and discuss insights and opportunities for future research.

2. Conceptual Model of Previous Fire Effects on Subsequent Fires

There are a number of pathways by which previous fires may affect suppression expenditures; some of these pathways may result in lower expenditures and others in higher expenditures. We conceptually model these pathways by considering three types of effects: The effect of previous fires on subsequent fire behavior and thus fire size and duration, the effect on management decisions to change suppression effort, and the effect of changes in suppression effort on fire size and duration. Figures 1–3 visually explain these pathways.

2.1. Fire Limiting Effect, No Change in Suppression Effort

Interactions with a previous fire could alter fire behavior such that the size, severity, or duration of the incident changes. Evidence suggests that interactions with previous fires tend to reduce the size and severity of subsequent fires [1–10]. Absent any changes in management strategy and to the extent that suppression expenditures scale with fire size and duration, this "fire limiting" effect would tend to reduce expenditures relative to fires that do not interact with previous fires, though the effect might be observable only in the reduction in fire size or severity. In the instance that previous fires do not alter fire behavior in a way that affects the size and duration of subsequent fires, expenditures relative to fires without previous fire interactions would be unchanged. See Figure 1 for the possible pathways exploring only the fire limiting effect.

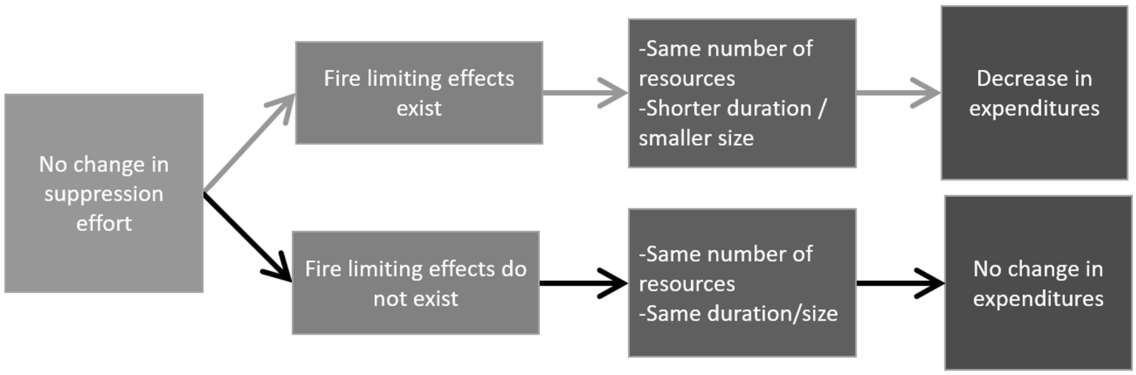

Figure 1. Pathways to changes in expenditures assuming no management change and exploring only possible fire limiting effects. Each arrow color indicates a single pathway. The left-most boxes indicate the change in management decisions, the middle-left boxes indicate the previous fires' physical effect on the subsequent fires' behavior, the middle-right box indicates the outcome of the change in management decision and the previous fires' physical effects in resource usage and fire behavior and the right-most box indicates the change we would expect to see in suppression expenditures.

2.2. Increase or Decrease in Suppression Effort, No Effect of Suppression Effort on Fire Size or Duration

Previous fires may also affect how fires are managed, resulting in changes to the strategy and intensity of suppression effort. Fire managers are often aware of past fires, may anticipate changes in fire behavior or control opportunities, and therefore may proactively alter strategic choices. For example, existing decision support systems used in the United States map the perimeters and dates of past fires in relation to the current fire, and fire behavior analysts will often adjust fuel models to account for the presence of the past fires [46]. From an operational perspective, previously built fire control lines can be used to serve as control locations, such that the length of previously burned perimeter can influence strategies and tactics.

We assume that fire managers form expectations of how previous fires will affect fire behavior and the marginal effectiveness of suppression resources for achieving management objectives. We also assume in this case that additional suppression effort does not alter the size and duration of the incident although it may affect other management objectives. There are two competing effects that may be at play here: increased suppression opportunities versus increased opportunity to monitor rather than engage. More specifically, managers may respond to the existence of previous fires in one of two ways: increase effort (i.e., assign more suppression resources per day) because previous fires offer the opportunity to safely engage the fire with more resources; or decrease effort (i.e., assign fewer resources per day) because the reduced chance that the fire will negatively affect values at risk allows managers to monitor the fire with fewer resources.

Here, we define effectiveness as a decrease in the size and/or duration of a fire resulting from an increase (on the margin) of resources assigned to a fire or effort expended with a given assignment of resources. In the case where managers increase suppression effort but such effort is not effective, the effect on expenditures is ambiguous; increased assignment of resources increases expenditures per day on average, but the fire limiting effect of previous fires may still reduce expenditures. Expenditures are expected to increase if the suppression effort effect outweighs the fire limiting effect and to decrease if the suppression effort effect is less than the fire limiting effect. In the case of reduced suppression effort, both the fire limiting effect and the reduction in commitment of resources operate in the same direction to reduce expenditures. See Figure 2 for the full set of pathways exploring possible effects given a change in suppression effort and non-effective suppression.

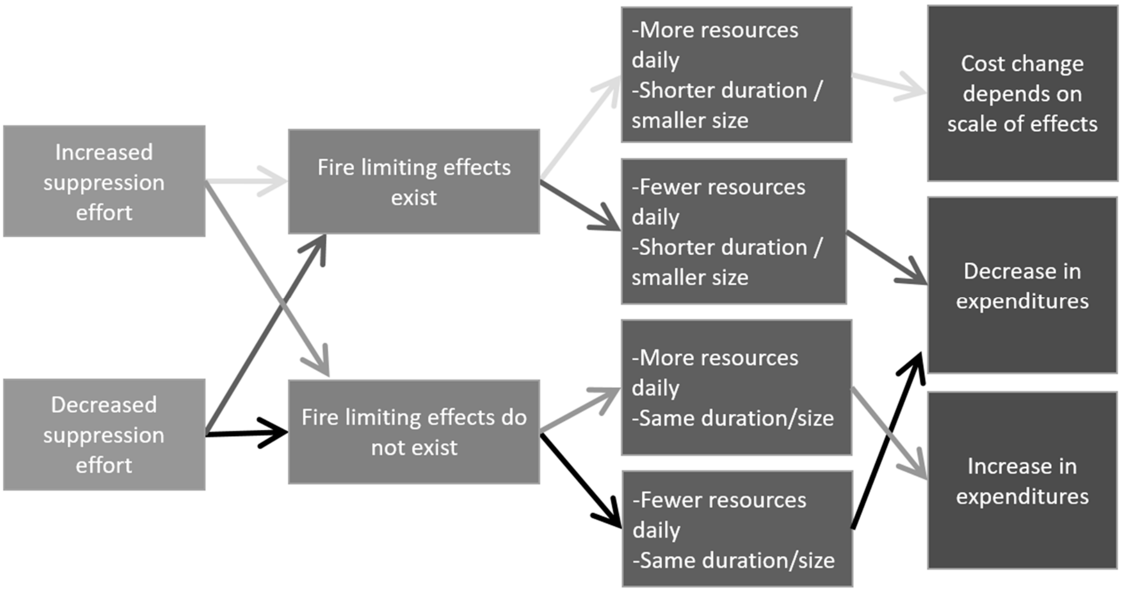

Figure 2. Pathways to changes in expenditures assuming management changes in response to previous fires, but the extra suppression effort has no effect on fire size or duration. Each arrow color indicates a single pathway. The left-most boxes indicate the change in management decisions, the middle-left boxes indicate the previous fires' physical effect on the subsequent fires' behavior, the middle-right box indicates the outcome of the change in management decision and the previous fires' physical effects in resource usage and fire behavior and the right-most box indicates the change we would expect to see in suppression expenditures.

2.3. Increase or Decrease in Suppression Effort, Suppression Efforts are Effective at Limiting Fire Size and Duration

The role of previous fires becomes more complex if we allow for suppression efforts to have an effect on the size and duration of incidents. The evidence on the effectiveness of suppression efforts to alter fire size and duration is mixed, and gaps exist in understanding of how fuel treatments, previous burns, and suppression efforts relate to fire outcomes. Research to date hasn't examined how the number or effort of suppression resources influences incident outcomes, and there is limited understanding of how fuel treatments and previously burned areas may alter suppression effectiveness (see [47] for a thorough summary suppression effectiveness research). With effective suppression (as defined in this study), increases in effort will tend to reinforce the fire-limiting effect of previous burns (i.e., smaller and shorter duration fires), and decreases in effort will tend to offset the fire-limiting effect. As in the previous section, with effective suppression the effect of previous fires when managers increase their suppression effort is ambiguous, depending on the relative size of the suppression and fire-limiting effects on fire behavior (negative) and the suppression effort effect on daily resource usage (positive) on expenditures. Similarly, the effect of previous fires when managers decrease suppression is ambiguous, depending upon the relative size of the suppression effect on fire behavior (positive), the fire limiting effect on fire behavior (negative) and the suppression effort effect on daily resource usage (negative). See Figure 3 for the full set of pathways exploring the possible effects on expenditures given a change in suppression effort and effective suppression.

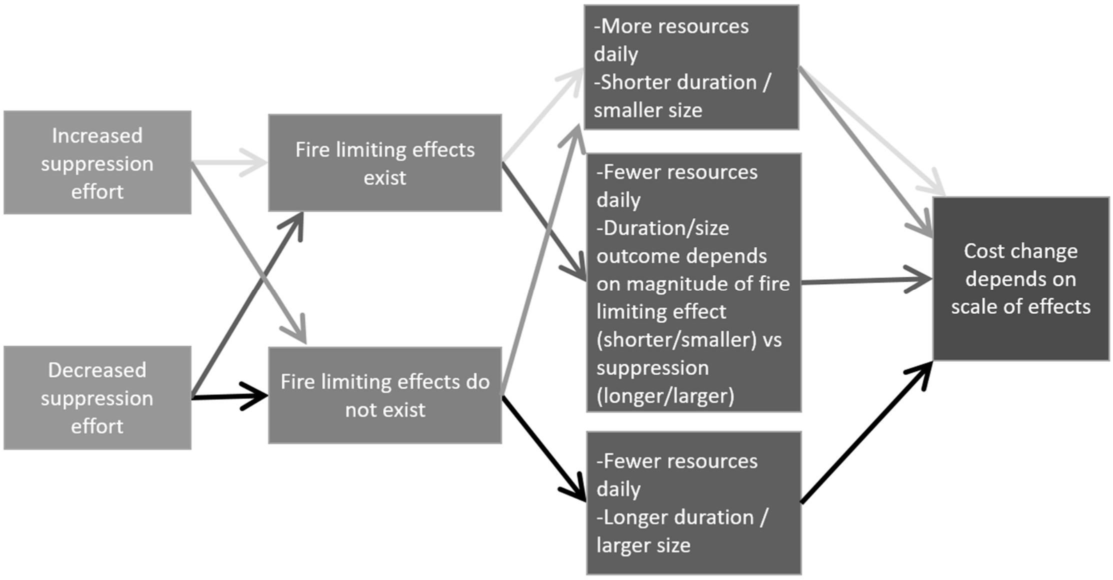

Figure 3. Pathways to changes in expenditures assuming management changes in response to previous fires, where the extra suppression effort is effective at changing fire behavior. Each arrow color indicates a single pathway. The left-most boxes indicate the change in management decisions, the middle-left boxes indicate the previous fires' physical effect on the subsequent fires' behavior, the middle-right box indicates the outcome of the change in management decision and the previous fires' physical effects in resource usage and fire behavior and the right-most box indicates the change we would expect to see in suppression expenditures.

2.4. Summary of Conceptual Model Pathways and Hypotheses about Expenditures

Given the multitude of pathways and their outcomes, the conceptual model makes clear that the effect of previous fires on subsequent suppression expenditures is, a priori, ambiguous. Our empirical analysis starts from the null hypothesis that previous fires have no effect on expenditures. Testing whether previous fire interactions results in higher, lower, or no difference in expenditures along with corresponding effects on fire size can provide evidence of which pathways may be driving expenditures and which effects are most important. For example, observing a clear increase in expenditures related to previous burns can rule out the possibility only the fire limiting effect plays a role, or that the combined effect of the fire limiting effect and suppression on fire size and duration is large enough to offset the increase in suppression effort. Similarly, observing a decrease in expenditures rules out the possibility that increases in suppression effort outweigh a fire-limiting effect or suppression effect on size and duration. In addition, our analyses of the effects of previous fires on subsequent fires' behavior (here we use fire size) allow us to further explore which pathways are consistent with empirical data.

3. Materials and Methods

3.1. Models

Our initial analyses examined the effect of previous fire interactions on fire size; this allowed us to test if we could eliminate any of the causal segments in Figures 1–3 connecting fire suppression decisions and fire size. It also allowed us to examine if interactions with previous fires had any detectable effect on fire behavior (size, in this case). To examine the effects of previous fire interactions on fire size we used a linear regression model fit using the ordinary least squares method.

$$\ln(hectares)_i = \beta X_i + \epsilon_i \tag{1}$$

The model in Equation (1) uses the following notation: $\ln(hectares)_i$ is the natural logarithm of the fire size measured in hectares for fire i, X_i is the matrix of observations of independent variables associated with fire i that we hypothesize may impact fire size (see Table 1 for the full list of variables), β is the vector of estimated coefficients for each independent variable, and ϵ_i is the error associated with the model fit for fire i (assumed to be normally distributed).

We then used the regression framework laid out by [29] to examine the effect of previous fires on subsequent suppression expenditures, using two-stage least squares (2SLS), instrumental variables framework. This framework allows us to directly estimate the effect of previous fires on fire size and then separately examine the effect of previous fires on suppression expenditures. The instrumental variables framework was chosen to account for the possible endogeneity of fire size and expenditures, i.e., suppression expenditures may represent a suppression effort that has an effect on fire size; failing to account for such a relationship may result in biased estimates of the effect of fire size on expenditures. The instrumental variables method allows us to estimate the effect of size on expenditures independent of suppression effort provided that suitable variables that predict fire size but not expenditures can be identified.

The literature on endogeneity of final fire size to suppression expenditures is mixed, with some research failing to reject exogeneity [27,44] and other research finding evidence to reject exogeneity [26]. Based upon the results presented by [29] and the instrumental variables suggested by [26,44], we fit the linear regression using a two-stage least squares method with fire size specified as endogenous and the following variables specified as instruments for fire size but excluded from the second stage expenditures regression: fire duration, year of ignition, the natural log of distance to the nearest city with a population of 250,000, ignition during September, October, or November (SON), and an interaction between SON and a region 5 (California) dummy variable.

$$\ln(totexp)_i = \beta X_i + \epsilon_i \tag{2}$$

The base model is shown in Equation (2) where $\ln(totexp)_i$ is the natural logarithm of the total agency suppression expenditures on fire i, X_i is the matrix of observations of independent variables associated with fire i that we hypothesize may impact suppression expenditures (see Table 1 for the full list of variables), β is the vector of estimated coefficients for each independent variable, and ϵ_i is the error associated with the model fit for fire i. The first stage fire size model is specified the same way as the fire size model presented in Equation (1), where the matrix X_i includes instrumental variables (noted in Table 1). For both the fire size model and the suppression expenditures model we clustered standard errors by the Forest Service region in which they occurred and by year the fire burned. The regression models were run in Stata [48].

There are multiple ways in which previous burns might affect suppression operations; interactions can be defined in terms of perimeter overlap and pre-burned area overlap (see Figure 4 for examples of perimeter overlap and pre-burned area). Pre-burned area interactions may moderate fire behavior allowing managers more opportunities for suppression and /or an opportunity to monitor the fire due to decreased risk whereas perimeter overlap may indicate fireline reuse, i.e., providing additional suppression opportunities. In addition, fires that interact with previous fires may be inherently different from those that do not. These different mechanisms through which previous fires may interact are crucial to differentiate. Thus, characterizing the previous fire interactions both by preburned area and perimeter overlap allow us to more closely examine our conceptual pathways empirically.

Table 1. Variable names, descriptions, sources and notes for the original regression framework outlined by [29]. Data sources: FFIS—Foundation Financial Information System, which is being replaced by the Financial Management Modernization Initiative (FMMI), available at http://info.fmmi.usda.gov/, accessed 9/3/2013. NIFMID—National Interagency Fire Management Integrated Database, maintained at the USDA National Information Technology Center in Kansas City, MO; NIFMID variables are self-reported by managers for each wildfire. NIFC FTP—available at ftp://ftp.nifc.gov/Incident_Specific_Data/, accessed 7/24/2013; WFDSS—Wildland Fire Decision Support System databases available at http://wfdss.usgs.gov/wfdss/WFDSS_Data_Downloads.shtml, accessed 7/24/2013; LANDFIRE—version 1.2.0 available at http://www.landfire.gov/lf_120.php, accessed 7/24/2013; LANDFIRE may not account for post-fire fuel transitions that occurred prior to 2010 and after the previous version of LANDFIRE (in 2008), although minimal changes in fuel shares are evident for the sample of fires used here.

Variable	Description	Source	Instrumental variable
lnexp	Natural log of total federal suppression expenditures in constant 2012 $ (Dep. Var.)	FFIS	
ln_hectares	Natural log of area (in hectares) within final fire perimeter	NIFC FTP	
erc_max	Maximum relative ERC percentile observed during the fire within the final perimeter	GIS calculation of data from [49]	
erc_std	Standard deviation of relative ERC observed during the fire within the final perimeter	GIS calculation of data from [49]	
ln_elevation	Natural log of the average elevation within the final perimeter	LANDFIRE	
wild_burn	Burned within Wilderness area (binary)	WFDSS	
wild_share	Share of final burned area within a Wilderness area	WFDSS	
IRA_burn	Burned within an Inventoried Roadless Area (binary)	WFDSS	
IRA_share	Share of final burned area within an IRA	WFDSS	
SDA_burn	Burned within other specially designated area (binary)	WFDSS	
SDA_share	Share of final burned area within a SDA	WFDSS	
slope_0_20	Share of final burned area with slope less than 20% (omitted reference category)	LANDFIRE	
slope_20_40	Share of final burned area with slope between 20% and 40%	LANDFIRE	
slope_40_60	Share of final burned area with slope between 40% and 60%	LANDFIRE	
slope_60_80	Share of final burned area with slope between 60% and 80%	LANDFIRE	
slope_80_100	Share of final burned area with slope greater than 80%	LANDFIRE	
usfs_share	Share of final burned area in USFS ownership	WFDSS	
doi_share	Share of final burned area in Dept. of Interior ownership	WFDSS	
grass_share	Share of final burned area with grass fuels	LANDFIRE	
brush_share	Share of final burned area with brush fuels	LANDFIRE	
timber_share	Share of final burned area with timber fuels	LANDFIRE	
slash_share	Share of final burned area with slash fuels	LANDFIRE	
ln_house_val_in	Natural log of housing value within the final perimeter in constant 2012 $1000	U.S. Census	
ln_house_val_5	Natural log of housing value within 5 miles of final perimeter in constant 2012 $1000	U.S. Census	
ln_house_val_10	Natural log of housing value between 5 and 10 miles from perimeter in constant 2012 $1000	U.S. Census	
ln_house_val_20	Natural log of housing value between 10 and 20 miles from perimeter in constant 2012 $1000	U.S. Census	
aspect_N_E	Share of final burned area with North, Northeast, or East aspect	LANDFIRE	
aspect_SE_SW	Share of final burned area with Southeast, South, or Southwest aspect	LANDFIRE	
aspect_W_NW	Share of final burned area in West or Northwest aspect (omitted reference category)	LANDFIRE	
duration (top-code)	Fire duration top-coded at 90 days	NIFMID	Instrumental variable
region1	Northern region identifier (binary, omitted reference category)	NIFMID	
region2	Rocky Mountain region indicator (binary)	NIFMID	
region3	Southwest region indicator (binary)	NIFMID	
region4	Great Basin region indicator (binary)	NIFMID	
region5	California region indicator (binary)	NIFMID	
region6	Northwest region indicator (binary)	NIFMID	
year06	Year 2006 indicator (binary, omitted reference category)	NIFMID	Instrumental variable
year07	Year 2007 indicator (binary)	NIFMID	Instrumental variable
year08	Year 2008 indicator (binary)	NIFMID	Instrumental variable
year09	Year 2009 indicator (binary)	NIFMID	Instrumental variable
year10	Year 2010 indicator (binary)	NIFMID	Instrumental variable
year11	Year 2011 indicator (binary)	NIFMID	Instrumental variable
SON	Fire ignition during September, October, or November (binary)	NIFMID	Instrumental variable
ln_neardist	Natural log of distance to the nearest city with a population of more than 250,000	U.S. Census	Instrumental variable

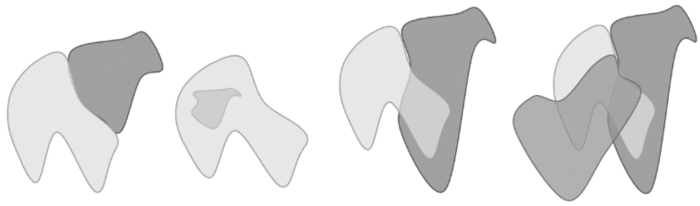

Figure 4. Examples of how previously burned fires may overlap with subsequent fires.

To accommodate the multiple ways in which interactions with previous fires needed to be defined and specified for our empirical model we added seven new variables; these specifically incorporate information into the regression model regarding if the fire had encountered a previous fire at all (binary), the percentage of the area of the subsequent fire that was pre-burned by a previous fires, and the percentage of the perimeter of the subsequent fire that overlaps with previous fire perimeters (see Table 2 for specific variables). We classified these percentages by the length of time since the previous fire occurred, as the number of years between a previous fire and a subsequent fire might influence the effect on the subsequent fire. For example, the footprint of a fire that occurred one year ago is likely to contain fewer fuels and any suppression line along the fire's perimeter is more likely to still be intact than a fire that burned ten years ago. To address this, we categorized previous fires into those occurring 0–5, 6–10, and 11–20 years prior to the subsequent fire.

Table 2. New variables that were added to the Hand (2016) model of suppression expenditures.

Variable Category	Time since Previous Fire Occurred	Variable Type (Range)	Variable Name
% area	0–5 years	Continuous (0–1)	% area 0–5 yrs
% area	6–10 years	Continuous (0–1)	% area 6–10 yrs
% area	11–20 years	Continuous (0–1)	% area 11–20 yrs
% perimeter overlap	0–5 years	Continuous (0–1)	% perimeter 0–5 yrs
% perimeter overlap	6–10 years	Continuous (0–1)	% perimeter 6–10 yrs
% perimeter overlap	11–20 years	Continuous (0–1)	% perimeter 11–20 yrs
Any previous fire interaction	0–20 years	Binary (0/1)	Prev fire (binary)

3.2. Spatial Data Preparation

We gathered data on suppression expenditures and the associated spatial traits for a subset of the large fires managed primarily by the USDA Forest Service (and thus most fires occur primarily on Forest Service lands) in western regions (i.e., Forest Service regions 1–6) exceeding 121 hectares from 2006 through 2011. The majority of the data used to fit this model was already processed for use fitting the models in [29]. We added 104 fires to the data in [29] that were not available when that study was conducted, and another 212 fires from previous years that had been excluded due to geospatial mismatches that could now be correctly matched. The previously processed data was drawn from a variety of databases including [49] (daily 4 km^2 geospatial raster observations), the Wildland Fire Decision Support System (geospatial polygon data), Landfire (a blended network of remotely sensed geospatial 30 m^2 raster observations, reference plots, and integrated records of vegetation disturbance), the US Census (geospatial Census block observations) and the national Interagency Fire Management Integrated Database (non-spatial manager-reported observations). Spatial processing matched these data with the area within the final fire perimeter. See [29] for more details regarding the processing and sourcing of each variable in the dataset.

To quantify interactions with past fires by area pre-burned and perimeter overlap we used data from the Monitoring Trends in Burn Severity (MTBS) national fire polygons layer developed from LANDSAT classified imagery [45], which is a set of remotely sensed geospatial 30m^2 raster observations). The 2017 product maps fires current to 2015 and corrects polygon shapes for Landsat 7 scan line errors. At the time of printing, a similar correction was not available for fire severity data. Although there are currently several spatial data sources for mapping fire polygons, MTBS is the most consistent methodology with reasonable spatial resolution (30 m) and time series length (1984 to 2016). The fires in this study were limited to the western half of the continental United States where MTBS had records of all fires greater than 400 hectares. Interactions between fires with expenditure data (between 2006 and 2011) and MTBS fires that occurred previously (pre-burn) were constrained by the temporal depth of the MTBS record, however the influence of previous fires on current fire behavior is also known to be temporally limited [7]. Thus, we only considered previous fires that occurred within 20 years of the subsequent fire, resulting in a data set with subsequent fires from 2006–2011 that are matched to previous fires burning 20 years prior to the subsequent fire's occurrence. All spatial buffering was accomplished using ArcMap [50]. The buffered values were then processed using a script developed in Python [51].

Due to mapping inconsistencies between the original fire perimeters [29] and MTBS fire perimeters, the MTBS versions of fire perimeters were used to represent all fires greater than 400 hectares in the spatial analysis. To identify pre-burned areas, we ran spatial statistics (overlapping area and length of perimeter intersect) for all MTBS fires intersecting and predating a fire in the model. Pre-burned areas were further binned by time since fire to assess the effect of temporal variability in interactions with previous fires both for pre-burned area and perimeter overlap. If an area was burned by more than one previous fire the area was attributed to the most recent fire (see Figure 4 for an example of multiple previous fires overlapping). Multiple pre-burn polygons from a single fire interaction were summed and calculated as a proportion of the total fire area. To account for spatial co-registration errors in MTBS perimeter mapping, fire perimeters were buffered by 30 m and interactions between only the buffered areas of fire perimeters were considered perimeter-only interactions. Lengths of these intersecting buffer polygons were calculated and summed to calculate fire-specific perimeter overlap. These values were then summarized as a fraction of the total fire perimeter (control line) reused during subsequent fires.

About half of the fires in the data had no pre-burned area and no perimeter overlap; of 722 fires 372 had neither pre-burned area nor perimeter overlap, 262 had both pre-burned area and perimeter overlap, 31 had perimeter overlap only and 57 had pre-burned area only. To ensure that the models were not biased by the high volume of zeros, we ran the models using two main datasets: the dataset of all 722 fires and the dataset of the 350 fires that had encountered a previously burned fire. However, we found the difference between datasets had little effect on the implications of the results; thus, we present the models using the full dataset. The other models are available from the authors upon request.

We were concerned about possible collinearity between perimeter overlap and area burned. The correlation matrix is presented in Table 3; with only one correlation over 0.5 and all but two correlations under 0.35, we found little evidence that a correlation would cause interpretability errors for our model.

Table 3. Correlation matrix for the percent area pre-burned variables and percent perimeter overlap variables.

	% Area 0–5 yrs	**% Area 6–10 yrs**	**% Area 6–10 yrs**	**% Area 0–5 yrs**	**% Area 6–10 yrs**	**% Area 6–10 yrs**
% Area 0–5 yrs	1.00	0.46	−0.07	−0.08	−0.11	−0.05
% Area 6–10 yrs	0.46	1.00	−0.04	−0.04	−0.11	−0.09
% Area 11–20 yrs	−0.07	−0.04	1.00	0.32	−0.08	0.02
% Perimeter 0–5 yrs	−0.08	−0.04	0.32	1.00	−0.10	0.05
% Perimeter 6–10 yrs	−0.11	−0.11	−0.08	−0.10	1.00	0.62
% Perimeter 11–20 yrs	−0.05	−0.09	0.02	0.05	0.62	1.00

4. Results

4.1. Regression Parameters

The coefficients on the fire interaction variables and model fit statistics for the linear regression model predicting fire size and for the second stage of the 2SLS model predicting suppression expenditures are presented in Table 4. The full model (all coefficients) are presented in the Appendix A. We tested the 2SLS model for exogeneity of fire size on suppression expenditures; the null hypothesis that the fire size variable is exogenous to suppression expenditures could not be rejected (Wald F statistic with 1 and 35 degrees of freedom: 1.804, p-value of 0.1879). We found that several of the instrumental variables were significant in the prediction of fire size; in particular, duration, burned in 2009, burned in 2010, and burned in 2011 were significant at the 95% level (the R^2 value for the first stage of the 2SLS model was 0.531). Although we cannot confidently reject exogeneity of fire size on suppression expenditures we did run an ordinary linear regression on suppression expenditures where fire size is included assuming exogeneity and all of the instrumental variables were excluded. The results were very similar, with percent perimeter overlap from 0-5 years prior having the largest effect (coefficient of 0.667, p-value of 0.037). All other variables had weak effects (p-values of 0.115 to 0.993).

Table 4. Regression parameter estimates for the model predicting fire size and the second stage of the 2SLS model predicting suppression expenditures. Standard errors are adjusted for 36 year-region clusters. Coefficient significance indicated as follows: * indicates significance at the 90% level, ** indicates significance at the 95% level, *** indicates significance at the 99% level.

	Fire Size OLS		**Fire Expenditures 2SLS**	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
%_area_0_to_5	−1.288 *	0.758	0.862	0.828
%_area_6_to_10	−1.239	1.096	1.045 *	0.611
%_area_11_to_20	−0.611	0.756	1.317	0.899
%_perim_0_to_5	−0.749	0.545	0.843 **	0.365
%_perim_6_to_10	−0.442	0.550	0.034	0.512
%_perim_11_to_20	−0.778	0.529	0.183	0.608
binary_fire_interaction	0.873 ***	0.117	−0.420 *	0.224
R^2	0.5308		0.5846	
Root MSE	1.0954		1.2699	
F-statistic *p*-value	< 0.0001	χ^2 *p*-value	< 0.0001	

We are most interested in the implications of the coefficients of the seven new interactions with previous fires variables; for ease of interpretation these variables and their standard deviations have been graphed in Figure 5 for both the fire size model and the suppression expenditures model. For fire size, the coefficient on the binary variable indicating if an interaction with previous a fire occurred is positive and significant at the 0.99 level. This result is likely due to the fact that larger wildfires are more likely to actually encounter a previous fire. The coefficients on both the area pre-burned and perimeter overlap variables are negative with a small effect size and weak significance (p-values of 0.09–0.42). Thus, conditional on encountering a previous fire, higher percentages of area burned by a previous fire and perimeter overlap from a previous fire are associated with smaller fire sizes. This suggests that interactions with previous fires may be fire limiting, but inference is weak.

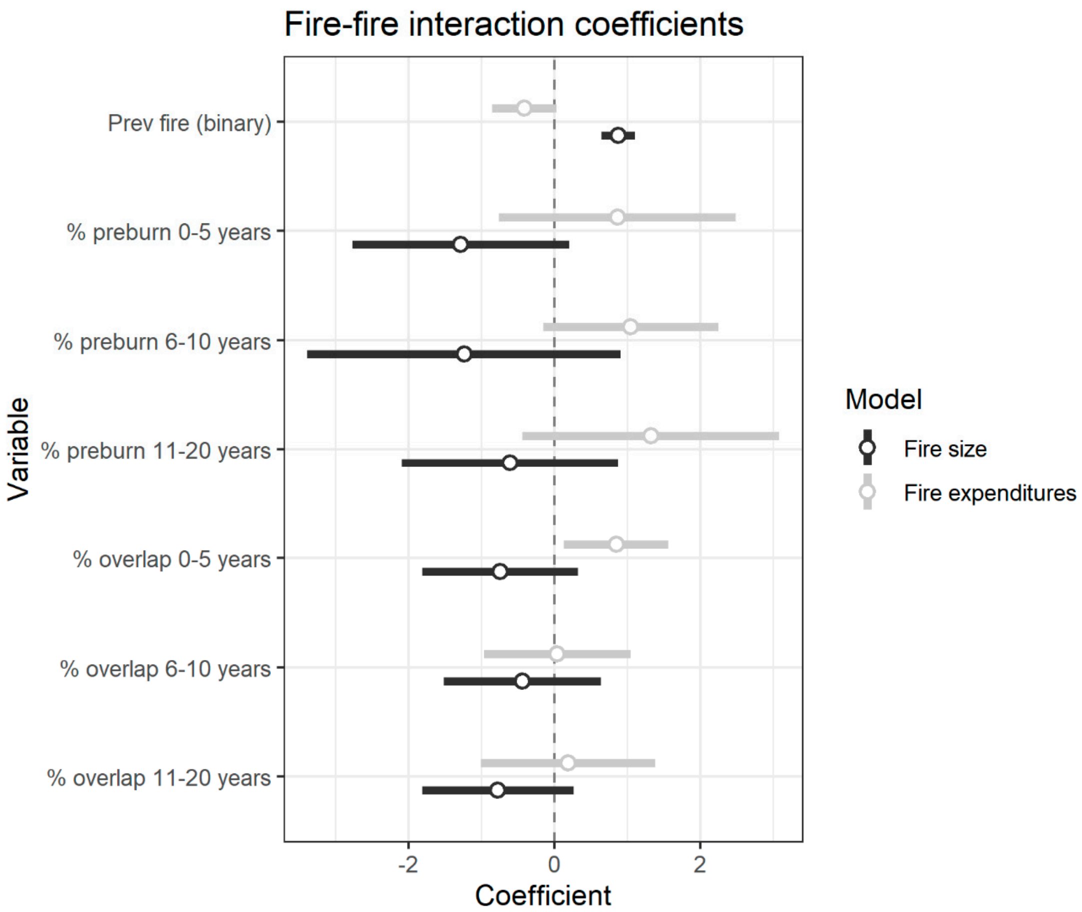

Figure 5. Coefficients and associated confidence intervals for the seven previous fire interaction variables as fit by the regression predicting fire size and the 2SLS regression predicting fire expenditures. The estimate of each coefficient is given by a point. The 95% confidence interval on each estimate is given by the line.

The coefficients for those variables in the suppression expenditures model were opposite of those from the fire size model. Similar to the fire size model, the effect indicated by the binary variable is the opposite sign of effects from the perimeter overlap and preburned area variables. Thus, there appears to be both a fire-wide effect and a marginal effect. Specifically, fires interacting with previous fires are significantly less expensive than those that do not (p-value of 0.02), even taking into account the larger size. Conditional upon encountering a previous fire, higher percent area preburned or perimeter overlap is associated with higher expenditures, though as with the fire size model inference is generally weak (p-values from 0.087–0.95) with the exception of the percent perimeter overlap burned from zero to five years ago (p-value of 0.02). The percent area pre-burned 6–10 years ago is the only other previous fire interaction variable significant at the 10% level.

4.2. Statistical Analysis of Fires that Interacted with Previous Fire

We further examined the data to see if there were any obvious trends that might explain the significantly positive relationship between expenditures and percent perimeter overlap from fires occurring 0–5 years ago. We were also interested in how the fires interacted with previous fires might be different than other fires (as indicated by the coefficients on the binary variable indicating an interaction with a previous fire). We formulated some hypotheses on why fires with a 0–5 year overlap interaction might be different to the rest of the fires and why those fires that have any interaction with previous fires might be different as well. With these hypotheses in mind, we examined the data using three main subsets: fires without any previous fire interaction, fires with previous fire interactions, and fires that had perimeter overlap with previous fires from 0–5 years prior.

Although the set of fires with perimeter overlap from fires within the past five years looks similar in many ways to the set of all the fires in regards to most of the explanatory variables (see examples of expenditures, size, share of wilderness, housing values inside the fire perimeter, share of timber and slash shown using density plots in Figure 6), there are a few key differences. The set of fires that have perimeter overlap from fires within the past five years are slightly larger, have less area in timber or slash, and a substantially higher proportion of the fires occurred in region five with a lower proportion occurring in region two. Thus, while the coefficients on the explanatory variables may stay consistent across the different sets of fires, it appears that fires with perimeter overlap from fires within the past five years are different from the larger pool of fires. This conclusion is supported by the significant positive coefficient on the binary variable indicating previous fire interactions in the model of fire size.

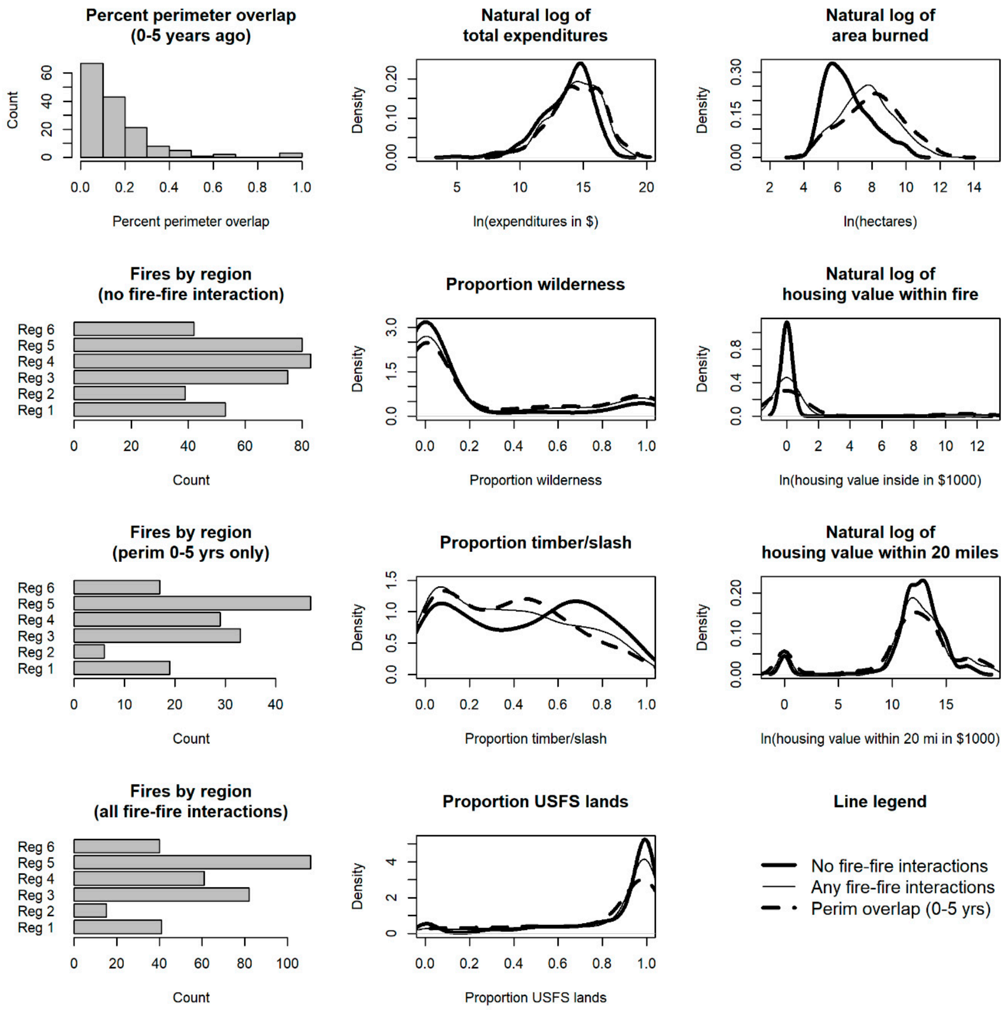

Figure 6. Comparisons of three main subsets of our suppression expenditure data: fires with no previous fire interaction (indicated by a thick solid line), fires with any previous fire interaction (indicated by a thin solid line), and fires with perimeter overlap from fires 0–5 years prior (indicated by a dotted line).

Additional probing into the pool of fires that had perimeter overlap from fires occurring 0–5 years ago reveals that the ten fires with the highest percent perimeter overlap were actually mid-size but slightly less expensive fires with a high housing value within 20 miles. In addition, six of these ten fires occurred in region five, two occurred in region three, and one occurred in each region four and region six. Region five has previously been identified as hosting more expensive fires [29]. These ten fires may be driving the coefficient on percent perimeter overlap from fires occurring 0–5 years ago.

5. Discussion

The results of our analyses provide suggestive evidence that previous fire interactions affect expenditures on subsequent fires, although we cannot rule out no effect of previous fire interactions with high confidence. Fires with interactions with previous fires are likely to be larger (p-value of < 0.001) but less expensive even after accounting for the larger size (p-value of 0.06); we discuss in the next paragraph why this does not necessarily imply that previous fire interactions cause larger fires. We find that, conditional on interacting with a previous fire, greater overlap with previous fire activity, either pre-burned area or perimeter, leads to no change in fire size or smaller sized fires (p-values of 0.09 to 0.42). In addition, we observe that while fires with previous fire interactions have overall slightly lower expenditures, each additional percentage of fireline that overlaps with previous fireline from the past five years increases expenditures by 0.85% (p-value 0.021). An increase in percent perimeter overlap with fires more than 5 years old (i.e., 6–20 years) appear to have no effect on expenditures (p-values between 0.76 and 0.95). Increases in the percent of area pre-burned for all three time periods are associated with increases suppression expenditures for all three variables, although the effects are imprecisely estimated (p-values between 0.087 and 0.30).

Looking at these results allows us to identify which pathways identified in Figures 1–3 are more influential. The positive effect of any previous fire interaction on fire size is likely caused by the fact that larger fires are inherently more likely to encounter a previous fire. If we accept this reasoning, then we can interpret the coefficients on the percent area pre-burned and percent perimeter overlap to indicate that area burned and perimeter overlap do generally have a fire limiting effect, which concurs with much previous research done on the effect of previously burned area on subsequent wildland fire behavior [1–10]. Given our analysis of the set of fires with interactions with previous fires, we believe they are inherently different than the set of fires without interactions with previous fires (i.e., they are inherently larger and less expensive as indicated by the binary variables in the 2SLS regression). Thus, we focus on the pathways that are consistent with the signs of the coefficients on the percent pre-burned area and percent perimeter overlap variables in the expenditures model. We can interpret these coefficients to indicate that given opportunities presented by perimeter overlap, managers do indeed increase the effort they put into the fire. In addition, the effect of the increased effort daily on expenditures is stronger than the possible gains from the increased effort's effect on shortening/shrinking the fire. We are left with one main pathway: that of fire limiting effects and a (possibly effective) increase in suppression on areas of the fire directly interacting with the previous fire (See Figure 7). This analysis does not imply that the other pathways do not occur, but rather that the other pathways do not appear to be the dominant pathways driving overall trends in fire size or suppression expenditures.

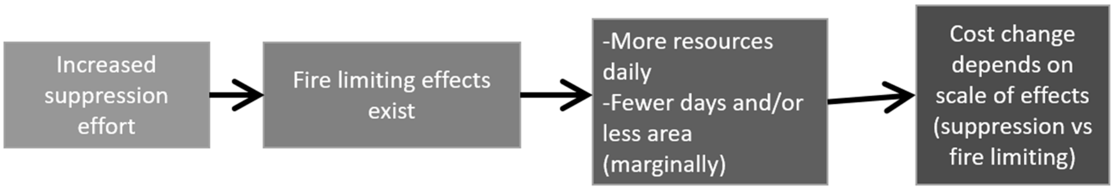

Figure 7. The pathways of our analyses indicating the dominant effects of suppression expenditures and size.

The key takeaway from this analysis is that we do not find evidence that interactions with previous fires reduce suppression expenditures for subsequent fires through the pathway of moderating fire behavior. Instead, the results suggest that previous fires may allow suppression opportunities that otherwise might not exist, resulting in an increase in suppression effort and increased expenditures. This implies, indirectly, that previous fires create conditions where suppression efforts can be effective, i.e., these efforts would not have been effective without the change in conditions. This is consistent with the economic framework laid out by [42], hypothesizing that fuel treatments may increase the marginal productivity of suppression, leading to greater suppression effort and higher suppression expenditures. However, our results are not precise enough to rule out no effect or small negative effects of previous fire interactions on expenditures with high confidence.

The model results do demonstrate that both of the two distinct types of previous fire interactions (i.e., perimeter overlap and pre-burned area overlap) may both play a role in influencing fire size and expenditures. Perimeter overlap is likely to correlate with an increased likelihood that fireline will hold due to increased ease of building/revitalizing the line or that particular fireline may have traits associated with it that increase the probability of the line holding even outside of fire behavior (for example, topographic features, see [52]). In contrast to the line specific effects that perimeter overlap is likely to reflect, pre-burned area is likely to affect suppression opportunities and fire size via fire behavior. The fact that pre-burned area increases expenditures on the margin is consistent with pre-burned area lowering severity, leading to increased suppression opportunities. Thus, these analyses are consistent with the findings by [12], who found evidence that fuel treatments from 0-3 years prior can limit wildfire size and intensity. These analyses also concur with the finding that fuel treatments generally increase suppression costs [43]. While [33] and [40] find suppression expenditures can go down when a fire encounters a fuel treatment, their analyses do agree with our results regarding the fire limiting effects but did not account for the increased suppression opportunities that may cause increased cost. Thus, our analyses indicate that increased suppression opportunities tend to lead to increased effort and thus increased expenditures.

Because our fire expenditures dataset is limited to large fires (greater than 121 hectares) and the previous fire interactions are limited to even larger fires (greater than 400 hectares), the effects appearing in our model are due to large fire interactions and do not account for the effects of smaller fires. Mapping methods used for small (under 400 hectares) fires with expenditure data (191 fires in our dataset were less than 400 hectares) typically rely on hand-held GPS tracks or aerial mapping, and yield similar enough results to the satellite imagery used by MTBS to allow reasonable previous fire interaction comparisons, however error accrued by these non-standardized methods tend to increase with fire size and perimeter length. It is also important to note that in calculating interactions with previous fires, unburned areas within a fire perimeter were not considered. The MTBS fire perimeter polygons dataset accurately captures perimeter location and total fire area but does not map internal un-burned or non-burnable locations. These data are included in the fire burn severity raster imagery but can be corrupted by scan line error anomalies.

Fire interactions were not considered during the year of the subsequent fire (i.e., between a subsequent fire and an adjacent fire that occurred during the same fire seasons). We assumed that two fires burning together during the same fire season were likely to be combined as a fire complex and would be recorded as a single fire. This is generally a safe assumption, however in 2018 in CA and UT there were several independent fires that interacted with one another. These fires were temporally spaced weeks apart (e.g., one fire was contained and then weeks later a different fire burned to the containment line from the opposite direction). When this is the case, there is no reburn, but perimeter overlap results in the fireline being reused. Thus, our data may have underreported the amount of perimeter overlap, but as these fires tend to be exceptions, we do not believe it has substantially skewed our analyses.

Our model results lead to the hypothesis that pre-burned area may decrease fire severity and thus increase suppression opportunities. Results also indicate that marginally increased preburned area is not associated with lower suppression expenditures, indicating that if managers are choosing to monitor fires with less severe fire behavior it is not substantially changing suppression expenditures. However, our model does not include data to specifically test if lowered burn severity is correlated with altered suppression expenditures, nor do we test if pre-burned area does, in fact, lead to lowered severity. A natural outcome of our results would be to obtain data regarding the severity of fires and include it in this modeling framework. Such work might address possible bias in the current incident management system towards suppression and ask: are we capitalizing on reduced intensity as an opportunity to put the fire out when it could be an opportunity facilitate burning with minimal damage but durable treatment effects?

In addition to contemporaneous fire effects, quantifying the benefit of expanded fire on the landscape could directly evaluate opportunities for future interactions with previous fires in light of findings here. All else being equal, the rate at which future fires would encounter current fires increases with area burned, and these encounters may afford more management opportunities. As with analysis of fuel treatments, estimating encounter rates would be a key determinant of efficacy of expanded burn rates, and would require evaluation of whether the likelihood of that area re-burning in a given time window is sufficiently high to change landscape-scale trajectories [15,40,53].

Our model does not include any data regarding suppression objectives, which could substantially affect suppression expenditures. For example, lowered fire intensity in the Wildland Urban Interface (WUI) could lead to increased suppression effort on point protection to save houses, particularly when outright fire containment is not possible. Because our results indicate that the interaction between suppression actions, fire behavior and expenditures is nuanced, further work on this topic is warranted, though data to examine these interactions are limited. Better documentation of incident decisions could allow for a more in-depth exploration of strategic decisions relating to past fire scars. Our model is also missing data regarding the incident command team managing the fire, which has been shown to significantly affect fire suppression expenditures [29]. Including such information in these regression models might provide further insight into the interactions between fire behavior and suppression effort.

The framework developed in our conceptual models and our results highlight that the effect of previous fires on expenditures is complex and worthy of further research. The conceptual set of pathways we developed may be useful to policy makers as a framework within which to consider the interactions between previous burned areas (including fuel treatments), suppression decisions, fire behavior outcomes, and final suppression expenditures. The research presented in this paper identified one pathway that currently appears to dominate the effect of previous fires on expenditures in our sample of 722 large fires from the western United States, i.e., fires that interact with previous fires are, on average, larger and less expensive though both increased area preburned and perimeter overlap are associated with decreased size and increased expenditures. Most of these marginal effects are small and imprecisely estimated. This research does not rule out that other pathways may be occurring, motivating future work examining these effects more closely.

Expanded monitoring and analysis of suppression operations is necessary not only to improve understanding but also to determine whether observed patterns remain consistent over time. There is some indication that large fire incident strategies are changing to emphasize more indirect approaches and use of pre-identified control locations [18,54], such that for instance the influence of percent of perimeter overlap may change. Similarly, the increased safety concerns associated with post-fire snag hazard [55] may foreclose opportunities for increasing suppression efforts within previously burned areas. We hope this empirical research helps to lay a foundation for continued economic analysis of wildfire management and the influence of past fires.

Supplementary Materials: The following are available at http://www.mdpi.com/2571-6255/2/4/57/s1

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Appendix A

The coefficients for all variables and model fit statistics for the linear regression model predicting fire size and for the second stage of the 2SLS model predicting suppression expenditures are presented in Table A1. We tested the 2SLS model for exogeniety of fire size on suppression expenditures; the null hypothesis that the fire size variable is exogenous to suppression expenditures could not be rejected.

Table A1. Regression parameter estimates for the model predicting fire size and the second stage of the 2SLS model predicting fire expenditures. Standard errors are adjusted for 36 year-region clusters. Coefficient significance indicated as follows: * indicates significance at the 90% level, ** indicates significance at the 95% level, *** indicates significance at the 99% level.

	Fire Size OLS		**Fire Expenditures 2SLS**	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
ln_hectares			0.894 ***	0.195
erc_max	0.024 ***	0.005	0.033 ***	0.011
erc_std	0.002	0.006	−0.021 **	0.009
ln_elevation	−0.170	0.116	0.798 ***	0.177
wild_burn	0.483 **	0.215	−0.142	0.248
wild_share	−0.365 *	0.220	−0.933 ***	0.334
ira_burn	0.976 ***	0.124	0.204	0.251
ira_share	−0.769 ***	0.169	−0.417	0.261
other_burn	1.260 ***	0.208	−0.369	0.417
other_share	−2.805	2.323	1.864	2.366
slp_20_40	−0.161	0.344	0.882 *	0.531
slp_40_60	−0.028	0.375	0.480	0.447
slp_60_80	0.356	0.776	1.182 **	0.590
slp_80_100	−1.682	1.346	1.180	1.103
usfs_share	−0.316	0.248	0.829 ***	0.287
doi_share	0.670	0.452	0.131	0.394
brush_share	−0.221	0.234	0.622 *	0.333
timber_slash_share	−0.376 *	0.215	0.951 ***	0.344
ln_house_val_in	0.103 ***	0.016	−0.027	0.030
ln_house_val_5	0.009	0.008	0.029 ***	0.008
ln_house_val_10	0.011	0.008	0.023 ***	0.009
ln_house_val_20	−0.012	0.010	0.030 **	0.014
asp_N_E	−0.010	0.289	0.449	0.434
asp_SE_SW	−1.010 ***	0.241	0.740	0.515
region2	0.460 **	0.194	−0.155	0.353
region3	0.693 ***	0.167	−0.155	0.291
region4	0.343 ***	0.119	0.161	0.341
region5	0.264	0.170	1.424 ***	0.308
region6	0.218	0.139	1.167 ***	0.320
%_area_0_to_5	−1.288 *	0.758	0.862	0.828
%_area_6_to_10	−1.239	1.096	1.045*	0.611
%_area_11_to_20	−0.611	0.756	1.317	0.899
%_perim_0_to_5	−0.749	0.545	0.843 **	0.365
%_perim_6_to_10	−0.442	0.550	0.034	0.512
%_perim_11_to_20	−0.778	0.529	0.183	0.608
binary_fire_interaction	0.873 ***	0.117	−0.420 *	0.224
fire_days	0.016 ***	0.002		
burned_in_2007	−0.035	0.119		
burned_in_2008	−0.180	0.117		
burned_in_2009	−0.661 ***	0.143		
burned_in_2010	−0.761 ***	0.108		
burned_in_2011	−0.328 **	0.136		
SON	0.053	0.190		
SON_region5	−0.214	0.358		
ln_dist_250k	−0.000	0.000		
constant	5.580 ***	0.715	−4.131 **	1.653
R2	0.5308		0.5846	
Root MSE	1.0954		1.2699	
F-statistic p-value	<0.0001	chi-sq statistic p-value	<0.0001	

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