Appendix A

Resource Personnel

Suppression resource data is reported as a quantity of single resource and strike team by resource type. A strike team is a defined set of resources with a common leader and communication. For example, a strike team may be composed of five engines crews with a single leader. We combine single resources and strike teams into a single measure of resource type in units of person-days dispatched to a fire.

Our objective is to empirically derive "weights" in terms of the number of personnel associated with a single resource and strike teams reported in the data. The data does include the quantity of active personnel assigned to the fire on the day of the report. We estimate a fixed effects regression of total active persons as a function of the single resource and strike team resources to derive appropriate weights for combining the two sets of variables. When resource j data is missing at time t within a fire for which another resource $-j$ data is non-missing, the missing observations are assumed to denote a lack of change in the number of resources committed to fire i and are filled by resource data at $t-1$. If there is no prior non-missing data, the observation is replaced with a zero. Without the replacement of intermittently missing data, the entire observation would be excluded from the estimation.

The regression coefficients in Table A1 represent the number of personnel associated with each resource reportedly dispatch to the fire. These estimates are consistent with documented staffing recommendations. We use the coefficient estimates to rescale the number of resources (hand crews, engines, etc.) into the number of personnel by day. We do not rescale aircraft.

Suppression Resource and Conditions on Other Fires

Our theoretical model suggests that the factors that influence demand on one fire also influence supply – the demand for suppression resources on other fires within the Geographic Area Coordination Center (GACC) region. We construct covariates that capture the effect of other fires, $-i$ on any particular fire i. We use data on fires $-i$, defined as other fires within the GACC under active management within 48 hours of the observation, to construct new variables

$j = \{Type\ 1\ Crew, Type\ 2\ Crew, Helicopter, Dozer, Engine, Threatened\ Homes\}$.

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 48 maximum value of a variable within a fire. The maximum value of the variable from each fire is then summed over all fires $-i$.

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

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 construction of resource and conditions on other fires creates serial correlation. The process we model is inherently dynamic, which should also lead to serial correlation. Our standard error estimates are robust to serial correlation.

Simulation Methods

We use the regression results to simulate the implications of a growing wildland urban interface on wildfire response resources and costs. This appendix provides details on the methods used to calculate the additional resource and cost estimates. The regression estimates provide a marginal impact of an additional threatened home on the number of personnel by resource type dispatched to a particular fire. We estimate the expected increase in the number of threatened homes using housing density projections at the US Census partial block group (Hammer et al. 2004). Specifically, we calculate the ratio of housing densities from 2030 to 2000 on each partial block group, which we use to scale up the number of reported threatened homes on fires in 2008. We use data from the 2008 fire season because it is representative of expected fire conditions in the future. We overlay fire ignition points provided in Short (2015) for all fires in the analysis that reported any threatened homes and calculate the maximum ratio of any partial block groups that lie within 2 kilometers of the ignition point. The additional number threatened homes (net of threatened homes reported in the dataset) on each day are multiplied by the regression coefficient estimates in the type 1 crew (0.015 with 90% confidence interval of [0.001, 0.028]) and engine (0.006 with 90% confidence interval of [0.001, 0.011]) models. Finally, we convert this estimated increase in personnel into units consistent with reported costs. Type 1 crews consist of 16.573 individuals and engine crews consist of 4.373 individuals on average as reported in Table A1. The estimates represent the additional number of resources dispatched to the fires in the dataset due only to an increase in the number of threatened homes.

We translate the estimated increased number of type 1 crews and engines into costs using the 2016 Standard Cost Components form used by the National Wildfire Coordinating Group to track daily costs on an incident (NWCG 2016). The daily cost of a type 1 crew in California is

$10,400 and $4,411 for an engine crew. Suppression resources are reported in the ICS-209 by relatively coarse resource types (i.e., engines). However, the cost of resources may vary from $1,600 to $4,800 by resource subtype defined by experience and expertise. Engines are divided into six types based on equipment, capacity, and intended objectives. Recent data has begun to break out the resource types by group. We use information on recent resource dispatch patterns to create a weighted average engine costs ($4,411). These daily costs are multiplied by the estimated additional resources assigned to the fire due to an increase in the number of threatened homes. The daily costs are then summed over all days within a fire, then over all fires within 2008.

The objective of the simulation is to provide context for the estimates, and not project the total cost of future wildfire response. By rescaling the number of threatened homes observed on historical fires, we implicitly assume that number and nature of fires in 2030 will be similar to past fires. Balch et al. (2017) and Radeloff et al. (2018) show that wildfire ignitions and behavior are correlated with spatial patterns of human development and activity. Moreover, climate change is expected to increase the frequency and severity of fires (Westerling et al. 2011). While we use an active fire season as the baseline for our simulation, we probably underestimate the threat to homes in the future with respect to fire occurrence and behavior.

Projecting California Fire Prevention Fee Revenue in 2030

We use the housing density projections to estimate additional revenue from the California Fire Prevention Fee in 2030 – a year prior to the reinstatement of the fee. We use GIS to find the US Census partial block group (Hammer et al. 2004) that intersect the California State Responsibility Areas (SRA) that are subject to the fee. The SRA shapefile is available on the

CalFire website at https://frap.fire.ca.gov/projects/sra_mapping/sra_2016_initial. We multiply the reported housing density growth from 2000 to 2030 by the calculated area of intersection of the block group and the SRA to find the total number of additional homes subject to the fire prevention fee. We multiply the projected number of homes by the low fee, $117, the high fee, $150, and the mean, $133, which provides total fee revenues.

Table A1. Coefficient Estimates for Person per Resource Model

	Coefficient	S.E.	P-value
Crew 1 (Single Resource)	16.573	2.795	<0.001
Crew 1 (Strike Team)	29.706	3.168	<0.001
Crew 2 (Single Resource)	12.568	2.371	<0.001
Crew 2 (Strike Team)	2.645	2.613	0.311
Aircraft	7.041	1.798	<0.001
Engine (Single Resource)	4.373	0.603	<0.001
Engine (Strike Team)	18.339	1.588	<0.001
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

Table A2. Coefficient Estimates from Resource Allocation Models

	Crew 1	Crew 2	Aircraft	Dozer	Engine
$Resource_{t-1}$	0.87***	0.576***	0.806***	0.683***	0.837***
	(0.119)	(0.185)	(0.104)	(0.226)	(0.06)
$Crew\ 1_{-i}$	-0.004	-0.003	<0.001	<0.001	0.004
	(0.009)	(0.007)	(0.001)	(0.002)	(0.012)
$Crew\ 2_{-i}$	-0.012	-0.011	-0.003	0.032	<0.001
	(0.282)	(0.213)	(0.004)	(0.037)	(0.104)
$Aircraft_{-i}$	-14.766	-3.709	-0.02	1.644	5.056
	(12.241)	(6.602)	(0.19)	(1.503)	(6.921)
$Dozer_{-i}$	1.79	0.254	-0.129	0.082	0.087
	(5.155)	(2.741)	(0.151)	(0.466)	(3.118)
$Engine_{-i}$	-0.513	0.151	-0.001	-0.032	-0.014
	(0.648)	(0.364)	(0.021)	(0.072)	(0.46)
$Threatened\ Homes$	0.016*	-0.006	>-0.001***	<0.001	0.007*
	(0.009)	(0.006)	(<0.001)	(0.001)	(0.003)
$Threatened\ Homes_{-i}$	-0.012*	-0.005	>-0.001***	<0.001	0.006
	(0.007)	(0.007)	(<0.001)	(0.001)	(0.012)
$Growth: Low$	-203.167	31.725	-3.581	-8.799	10.648
	(156.697)	(49.547)	(2.541)	(8.618)	(46.146)
$Growth: High$	-65.938	47.468	-3.733	-3.365	68.405
	(142.298)	(52.947)	(2.591)	(7.977)	(66.522)
$Growth: Extreme$	-87.88	24.568	1.227	12.707	105.613**
	(87.832)	(53.647)	(2.797)	(10.668)	(47.256)
$Percent\ Contained$	-0.093	-0.034	0.004	0.043	0.169
	(0.605)	(0.388)	(0.012)	(0.105)	(0.349)
$Day\ of\ Year$ (sin)	-4.485	-5.093	0.278	1.355	-4.721
	(19.342)	(9.306)	(0.411)	(2.082)	(9.152)
$Day\ of\ Year$ (cos)	-0.999	-13.643	0.006	2.562	2.469
	(20.166)	(12.217)	(0.408)	(2.462)	(13.952)
$Count\ (I)$	-2.359*	-0.308	-0.005	0.127	-0.756
	(1.242)	(0.757)	(0.031)	(0.137)	(0.631)
$Inaccess: High$	-1.632	-0.199	0.468	-0.726	-10.382
	(22.707)	(12.333)	(0.397)	(1.819)	(11.487)
$Inaccess: Extreme$	-1.14	-6.146	-0.335	-3.955*	-17.532**
	(18.013)	(13.146)	(0.517)	(2.262)	(8.913)
$PDSI$	-1.153	-1.2	0.032	0.56	0.924
	(2.466)	(1.556)	(0.06)	(0.515)	(1.96)
$Lightning$	0.009	-5.52	0.266	1.378	-10.786
	(21.868)	(11.577)	(0.446)	(1.601)	(7.885)
$Elevation$	-0.003	-0.002	<0.001	<0.001	-0.001
	(0.003)	(0.002)	(<0.001)	(0.001)	(0.002)
$Slope$	-0.238	-0.125	0.011	0.018	-0.052
	(0.317)	(0.195)	(0.009)	(0.04)	(0.148)

$Fuel\ Model: Grass$	19.271	2.99	-0.284	0.173	10.213
	(16.595)	(8.566)	(0.337)	(1.7)	(10.08)
$Fuel\ Model: Brush$	9.753	9.627	0.947*	4.108	12.209
	(15.52)	(10.946)	(0.519)	(3.23)	(8.859)
$Fuel\ Model: Slash$	14.052	-0.639	0.295	1.679	-0.726
	(16.484)	(16.875)	(0.336)	(2.353)	(10.523)
$Wilderness$	-3.682	0.831	-0.219	-0.506	2.834
	(16.962)	(11.8)	(0.374)	(2.158)	(12.189)
$lnMedValue$	10.032	3.884	0.275*	0.596	0.261
	(6.704)	(2.803)	(0.144)	(0.537)	(3.027)
$Hdensity20$	-0.001	0.008	<0.001	0.001	-0.023
	(0.036)	(0.022)	(0.001)	(0.005)	(0.027)
$lnDistance$	-0.163	-0.383	0.009	0.077	0.096
	(0.499)	(0.351)	(0.015)	(0.08)	(0.359)
$Year: 2004$	13.323	-14.069	-0.243	-1.514	1.948
	(19.313)	(13.244)	(0.541)	(2.415)	(14.159)
$Year: 2005$	4.49	-11.255	-0.594	-6.637*	-2.296
	(27.786)	(14.165)	(0.672)	(3.824)	(15.988)
$Year: 2006$	-8.881	-23.289	-0.809**	-4.364**	-2.855
	(15.192)	(16.136)	(0.382)	(2.204)	(10.503)
$Year: 2007$	-18.909	-17.896	-0.459	-1.159	2.322
	(19.181)	(18.706)	(0.403)	(1.897)	(9.287)
$Year: 2008$	6.382	-18.957	0.296	0.953	-5.637
	(29.113)	(16.076)	(0.725)	(2.617)	(11.484)
$Year: 2009$	-22.425	3.667	-1.004	-2.006	0.340
	(33.739)	(22.767)	(0.623)	(3.376)	(15.821)
$Year: 2010$	-13.352	-6.824	-0.015	-2.254	13.483
	(29.023)	(19.351)	(0.669)	(3.014)	(14.299)
$FS\ Region: North$	11.252	-20.052	-0.772	-0.64	-8.226
	(26.211)	(21.737)	(0.566)	(3.022)	(11.619)
$FS\ Region: Southwest$	18.602	-20.892	-1.163	-1.53	3.327
	(47.936)	(24.174)	(0.754)	(4.103)	(12.598)
$FS\ Region: Intermountain$	9.300	-7.707	-1.276	-4.459	-16.898
	(47.913)	(23.594)	(0.901)	(5.121)	(16.519)
$FS\ Region: California$	46.923	-23.576	-0.397	2.536	6.521
	(39.596)	(22.04)	(0.730)	(2.991)	(16.238)
$FS\ Region: Rocky\ Mountain$	19.044	-13.328	-0.540	-1.019	-6.912
	(30.164)	(20.799)	(0.6)	(3.782)	(15.759)
X^2 Statistic	4184	1692	4540	1235	10420
Hansen Test P-value	0.669	0.455	0.409	0.511	0.471
Instrument Lag Depth	(3:4)	(3:4)	(2:4)	(2:5)	(2:5)
Instrument Count	61	59	68	76	76
Lag 1 P-value	0.097	0.174	<0.001	0.200	<0.001
Lag 2 P-value	0.258	0.097	0.962	0.446	0.966
Lag 3 P-value	0.264	0.563	0.366	0.511	0.953

Lag 4 P-value	0.439	0.444	0.421	0.617	0.748
Lag 5 P-value	0.144	0.165	0.413	0.878	0.796
Lag 6 P-value	0.292	0.857	0.192	0.657	0.543
Lag 7 P-value	0.231	0.976	0.273	0.533	0.708

Fires=585; Observations=2,799; * p<0.1; ** p<0.05; *** p<0.01; s.e. in parentheses
Note: lags 1-7 are valid instruments if they are uncorrelated with $\bar{y}_t$