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Would you like to know more? The effect of personalized wildfire risk information and social comparisons on information-seeking behavior in the wildland–urban interface

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Abstract
Private landowners are important actors in landscape-level wildfire risk management. Accordingly, wildfire programs and policy encourage wildland–urban interface homeowners to engage with local organizations to properly mitigate wildfire risk on their parcels. We investigate whether parcel-level wildfire risk assessment data, commonly used to inform community-level planning and resource allocation, can be used to "nudge" homeowners to engage further with a regional wildfire organization. We sent 4564 households in western Colorado a letter that included varying combinations of risk information about their community, their parcels, and their neighbors' parcels, and we measured follow-up visits to a personalized "Web site". We find that the effect of providing parcel-specific information depends on baseline conditions: Informing homeowners about their property's wildfire risk increases information-seeking among homeowners of the highest-risk parcels by about 5 percentage points and reduces information-seeking among homeowners of lower-risk parcels by about 6 percentage points. Parcel-specific information also increases the overall response in the lowest risk communities by more than 10 percentage points. Further, we find evidence of a 6-percentage point increase in response rate associated with receiving a social comparison treatment that signals neighboring properties as being either low or moderate risk on average. These results, especially considered against the 13 percent overall average response rate, offer causal evidence that providing parcel-specific wildfire risk information can influence behavior. As such, we demonstrate the effectiveness of simple outreach in engaging wildland–urban interface homeowners with wildfire risk professionals in ways that leverage existing data.

Keywords Nudge · Information-seeking · Public engagement · Wildland fire · Personalized information · Social comparison

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1 Introduction

The social costs of wildfires are escalating due to climate change, past fuel and fire management decisions, and increased development in fire-prone areas (Theobald and Romme 2007; Moritz et al. 2014; Schoennagel et al. 2017; Radeloff et al. 2018). In the USA, the National Cohesive Wildland Fire Management Strategy provides a vision for the wildfire community "to work collaboratively among all stakeholders and across all landscapes, using best science, to make meaningful progress toward the three goals: 1. Resilient Landscapes, 2. Fire Adapted Communities, and 3. Safe and Effective Wildfire Response" (www.forestsandrangelands.gov/strategy/). This strategy encompasses policy at all levels of government before, during, and after a wildfire event. Community wildfire education and mitigation organizations have embraced the notion of Fire Adapted Communities (www.fireadapted.org) as a concept for designing and implementing wildfire mitigation and education programs that emphasize the importance of wildfire risk mitigation on private lands. Moving from concept to practice, wildfire mitigation and education organizations connect with wildland–urban interface (WUI) homeowners through mailings, community events, and other outreach efforts, with the goal of working directly with the homeowners to mitigate the risk of wildfire to their homes. Encouraged risk mitigation actions include the creation of "defensible space" (i.e., an area around a structure that has been designed and maintained to reduce fire danger) and "structural hardening" (i.e., using ignition-resistant building materials and designs) (Cohen 2008; Calkin et al. 2014).

Understanding what causes households to engage with community wildfire organizations and, ultimately, in risk mitigation activities, is less straightforward. Research demonstrates that homeowners' decisions about mitigation are complex and informed by economic, behavioral, and social considerations (Brenkert-Smith et al. 2006; McCaffrey et al. 2013; Meldrum et al. 2019). While WUI homeowners often recognize that they face wildfire risk generally (Cohn et al. 2008; McCaffrey et al. 2013), they also often note in surveys a lack of property-specific information as a barrier to risk mitigation actions (Meldrum et al. 2018), and they tend to perceive their properties' risk-related characteristics differently from how wildfire specialists do (Meldrum et al. 2015). Further, more mitigation activity has consistently been found among people who report interacting one-on-one with wildfire experts and receiving information from trusted sources (Sturtevant and McCaffrey 2006; Brenkert-Smith et al. 2012, 2013). Wildfire in the WUI is also characterized by risk interdependence (Kunreuther and Heal 2003), with evidence demonstrating the influence of both social (Brenkert-Smith et al. 2012, 2013; Dickinson et al. 2015, 2020) and spatial (Shafran 2008; Schulte and Miller 2010; Warziniack et al. 2019) interactions on decisions about wildfire risks. Here, motivated by research findings from other contexts, we ask whether providing WUI homeowners with their property-specific wildfire risk ratings, or with a social comparison based on their nearest neighbors' average wildfire risk ratings, can increase engagement with a regional wildfire organization, thereby helping overcome these barriers. Further, beyond simply asking whether information treatments increase overall engagement, we also ask who responds to our behaviorally informed risk communications and whether their response depends on the underlying risk levels.

Research in the field of behavioral economics suggests that the provision of specific information can act as a "nudge" to change behavior. A nudge is an intervention that capitalizes on behavioral biases and decision-making heuristics by changing the framing, context, or availability of information to steer decisions without changing choice sets or incentives (Thaler and Sunstein 2009). The potential for harnessing nudges to advance the public interest has garnered substantial attention (Madrian 2014; Thaler 2018), and nudges have been investigated in many publicly relevant domains, including energy conservation (Allcott and Mullainathan 2010; Price 2014), public health (Blumenthal-Barby and Burroughs 2012; Rice 2013), and personal finance (Madrian and Shea 2001; Knoll 2010). While the literature includes examinations of behavioral biases in decisions about risks and natural hazards in general (Tversky and Kahneman 1974; Kunreuther et al. 2013; Kunreuther and Pauly 2014), and wildfire risk in particular (Brenkert-Smith et al. 2006; McCaffrey et al. 2013; Wibbenmeyer et al. 2013; Bartczak et al. 2015; Dupéy and Smith 2018), the use of nudges to encourage risk mitigation behaviors has not yet been explored.

In this study, we test whether and how two simple informational nudges affect WUI homeowner engagement with a regional organization that provides wildfire risk mitigation education and support. We leverage existing parcel-level wildfire risk assessment data, which provide a quick snapshot of the conditions of individual residential properties pertinent to wildfire risk. Many local and regional organizations across the USA collect this type of data to support planning and allocation of resources. Less common are robust methods to leverage such data for increasing public engagement with these organizations. Given the paucity of policies mandating wildfire mitigation on private lands, voluntary homeowner engagement is critical for the successful fulfillment of these organizations' missions to reduce wildfire risk in the WUI. Moreover, wildfire risk mitigation is an involved process that often requires engagement with a formal wildfire organization to access financial resources and expert guidance. Figure 1 provides a conceptual illustration of how wildfire organizations often engage with WUI homeowners to encourage wildfire risk mitigation and how an informational nudge may supplement these efforts.

We randomly assigned households to receive one of three different versions of a mailing from a regional wildfire organization, which included either: (1) community-level risk information only, (2) community- and parcel-level risk information, or (3) community- and parcel-level risk information as well as the averaged risk information of neighboring parcels. The parcel-level risk rating acts as a personalized information treatment, which has effectively nudged behavior in other contexts. In particular, meta-analyses of public health literature demonstrate the effectiveness of tailored print (Noar et al. 2007) or text messages (Head et al. 2013) in producing small but significant behavioral changes over a wide array of study contexts. Likewise, Edwards et al.

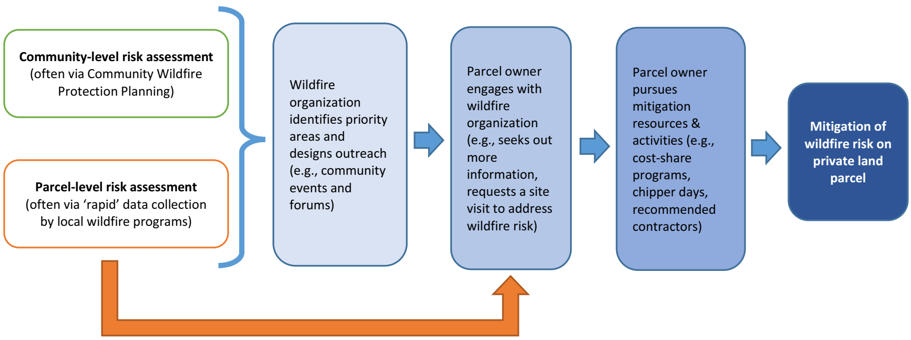

Fig. 1 Pathways to wildfire risk mitigation on private lands. Conceptual model of mitigation behavior change through traditional wildfire organization program delivery (blue arrows) and informational nudge (orange arrow)

(2013) reviewed 41 studies and found that personalized disease risk messages generally produced small increases in the number of related screening procedures undertaken. In other contexts, personalized information about prescription drug plan costs encouraged switching to lower-cost plans (Kling et al. 2012), and messages providing individualized information increased college entry for intending high school graduates (Castleman and Page 2015). Further, the perceived sufficiency and specificity of risk information have been associated with preparedness and risk mitigation actions for natural hazards (Griffin et al. 1999; Mileti et al. 2006).

The averaged neighboring parcel information acts as a second treatment, focused on social comparisons. Social comparisons have effectively nudged behavior in many other contexts, with perhaps the richest related literature concerning the provision of neighbors' average levels of household electricity use (Allcott 2011; Ayres et al. 2013; Brandon et al. 2018). The literature has found one's reference group to be relevant in determining the effect of personalized information and social nudges, although specific findings are not necessarily consistent across contexts: Social nudges have produced large reductions in energy use for households with high pre-nudge use but either negligible reductions (Allcott 2011) or even increased use (Schultz et al. 2007) for those with the low initial use levels, and they produce larger reductions in water consumption among those who initially consumed the most (Ferraro and Miranda 2013; Ferraro and Price 2013). Experiments have also shown that people are more willing to make charitable contributions if they know others have (Alpizar et al. 2008; Frey and Meier 2004), albeit with effects much stronger on those who otherwise appear most indifferent. Past experiments have also found that relatively low-paid workers react negatively to peer information regarding 401(k) enrollment and contributions, which the authors suggest is due to "discouragement from upward social comparisons" (Beshears et al. 2015). Another experiment disclosing peer salaries found differences in pay ranking to matter more than differences in pay levels (Card et al. 2012).

Here, we measure the effect of the treatments on homeowners' subsequent information-seeking behavior through visits to a customized "Web site". Specifically, homeowners entered a unique code from their nudge letter to access a "Web site" for their specific property, which also allows for tracking of individual responses. This "Web site" presents visitors with more detailed parcel-specific wildfire risk information and encourages further actions associated with wildfire mitigation. Such effortful information-seeking is predicted to influence risk attitudes and behaviors (Griffin et al. 1999), yet few studies in natural hazards identify causal links between interventions and behavioral outcomes rather than associations with attitudes or intentions. "Web site" visits represent household effort to address wildfire risk and constitute an important entry point into the pipeline of risk mitigation education and support provided by the practitioner organization (Fig. 1). Our response variable thus directly corresponds to homeowners taking an important step toward undertaking mitigation actions by seeking more thorough, property-specific information that will help them overcome observed barriers to such actions.

Overall, we find that 13% of homeowners seek further information across treatments but find no overall average effects from either of the information treatments. However, we find that both the personalized parcel-specific information and the social comparison information influence response rates for specific categories of risk ratings, with the direction of the influence depending on the specific content of the provided information. Accordingly, our study offers two main contributions to the natural hazards literature: (1) We demonstrate the effectiveness of a simple nudge in influencing risk information-seeking behavior in a hazards context, and (2) in our application, the behavioral response to risk information is dependent on the specific content of the risk information that is provided. Combined, these results suggest opportunities for wildfire organizations to leverage parcel-level risk ratings in communications that target the households facing the highest risks from wildfire.

2 Materials and methods

Our data come from a field experiment designed by the authors and implemented by West Region Wildfire Council (WRWC), a non-governmental organization that encourages, informs, and supports wildfire risk mitigation on private property in six counties in west-central Colorado (www.cowildfire.org). The experiment entailed mailing a nudge letter that was personalized with wildfire risk rating information and included an appeal for the recipient to visit a property-specific "Web site" for more detailed information ("Appendix" Figure a1). Households were randomly assigned to one of three groups to determine the information content that would be provided in their letter: (1) a letter that included only their community-level wildfire risk rating (Community), (2) a letter that included both their community-level and their parcel-level wildfire risk rating (Parcel), or (3) a letter that further included the average parcel-level wildfire risk rating of their 10 nearest neighbors (Neighbor). Treatment 1 refers to the provision of personalized Parcel information; for this treatment, the "treatment" group consists of the second and third groups, while the "control" group consists of the first group. Treatment 2 refers to the provision of the social comparison Neighbor information; for this treatment, the "treatment" group consists of the third group, while the "control" group consists of the second group. (The first group is omitted from analysis of the second treatment due to potential confounding with Treatment 1.) The letters were closely modeled on those found successful at encouraging water conservation in a past informational and social comparison nudge experiment (Ferraro et al. 2011).

The letter was signed by the WRWC wildfire mitigation specialist and the fire chief for the letter recipient's local fire department, and then mailed to 4564 WUI homeowners in seven fire protection districts in Delta, Montrose, San Miguel, and Ouray counties in western Colorado. All 4564 homeowners also were sent a follow-up letter, which contained the same substantive information as the first mailing, for a total of two mailings to each property. Due to WRWC's programmatic and other constraints, the second mailings were mailed anywhere from within a few weeks of the first mailing in some communities to about 1 year later in other communities. Regardless, the vast majority of "Web site" visits occurred within a few weeks of receiving either one of the mailings. All mailings were batched by community, meaning that all members of a specific community would receive their letters at the same time. Overall, mailings to different communities were staggered across August 2016 and June 2018 to smooth WRWC's workflow in fielding public response.

In developing the information treatments, the experiment leverages two sources of existing risk assessment data: (1) community-level ratings developed through the Community Wildfire Protection Plan process and (2) parcel-level ratings from WRWC's rapid wildfire risk assessment of each residential parcel with a structure in investigated communities. Community Wildfire Protection Plans, as defined by the Healthy Forest Restoration Act of 2003 (16 U.S. Code 6501), are developed collaboratively and agreed to by the local government, fire department, and other stakeholders. Since 2009, Colorado Senate Bill 09–001 has required all Colorado counties to have a plan for any identified fire hazard areas within their unincorporated areas. These must include, among other components, a community risk analysis narrative addressing fuel hazards, wildfire occurrence, and community values at risk (Colorado State Forest Service 2009). In the process, WRWC and other local stakeholders define WUI community boundaries and assign community-level risk ratings in one of the five categories (low, moderate, high, very high, and extreme) based on the results of this risk analysis narrative. This study includes households within 48 unique communities distributed across the seven fire protection districts.

For the parcel-level risk assessment process, WRWC assesses eleven characteristics that affect a home's wildfire risk. These characteristics include measures of defensible space, structural hardening, and other risk-related considerations. WRWC then assigns each parcel one of the five adjective risk ratings (low, moderate, high, very high, extreme) based on the weighted sum of scores reflecting these characteristics. Building on the Home Ignition Zone concept (Cohen 2000), the Bureau of Land Management and WRWC developed the parcel-level risk assessment process over a series of implementations. Similar tools are used widely in the fire adaptation community (Fire Adapted Communities Learning Network 2015).

These two sources of data provide two separate ratings (Parcel and Community, respectively) for each of the 4,564 properties in the study. The third separate rating (Neighbor) was assigned to each property in the study according to the simple average overall risk score of that property's 10 nearest neighbors, converted to an adjective rating as for the parcel-level assessment. Given the non-randomized nature of the context, in which the wildfire risk ratings reflect real-world characteristics of each property, we used a randomized block design to assign properties to treatment. Properties were divided into blocks according to their Parcel, Community, and Neighbor ratings. This ensures that assignment to different treatments is balanced across all combinations of rating levels and their relative positions to each other (e.g., parcel lower than community, parcel higher than community). This approach controls for pretreatment characteristics (in this case, risk levels) that could be expected to affect the response (information-seeking) by assigning treatments (types of information provided) within blocks, or subsets, of those characteristics. For example, if a low-risk parcel is less likely to seek information on mitigation than a high-risk parcel, regardless of treatment assignment, then ensuring equal distribution of treatments within low- and high-risk blocks will avoid confounding the effect of risk with the effect of the treatment.

Table 1 describes the sample sizes for the control and treatment group for a given comparison. Given the randomized block design, the associated sample sizes were not within the domain of experimental control once communities were selected for inclusion in the study. Relatedly, while the three sets of five rating categories lead to 125 possible combinations, only 95 of these are populated here due to few communities receiving either a low or an extreme community rating.

We estimate the effect of the information treatments on visits to a personalized "Web site". Specifically, we estimate main effects reflecting the overall effect of each treatment as well as treatment effects within each Community, Parcel, and Neighbor (if relevant) rating category using a series of t tests. We also estimate effects of the first treatment with a logistic regression model of the equation

$$
\begin{aligned}
y_i = \beta_1 Treatment_i + \beta_2 Community_i + \beta_3 \left(Treatment_i * Community_i\right) \\
+ \beta_4 Parcel_i + \beta_5 \left(Treatment_i * Parcel_i\right) + \epsilon_i
\end{aligned}
$$

where $y_i = 1$ if homeowner i visited the "Web site" and $y_i = 0$ otherwise, $Treatment_i = 1$ if the letter provided the personalized information (i.e., Parcel rating) and $Treatment_i = 0$ otherwise, $Community_i$ corresponds to a set of indicator variables for the Community ratings, $Parcel_i$ corresponds to a set of indicator variables for the Parcel ratings, and ϵ_i is an

Table 1 Sample size, response rate, treatment effects, and significance of personalized parcel-level risk information by Community rating levels (top panel) and Parcel rating levels (bottom panel)

	Sample size		Response rate		Treatment effect (percentage point)					
	Control	Treatment	Control	Treatment	Difference	95% interval		p value[A]	BH[B]	Effect size[C]
All	1492	3072	0.130	0.123	−0.007	−0.027	0.014	0.528		0.030
Community rating										
Low	48	189	0.042	0.148	0.106	0.030	0.183	0.007	*	0.110
Moderate	224	448	0.138	0.145	0.007	−0.050	0.063	0.814		0.080
High	668	1329	0.112	0.099	−0.013	−0.041	0.015	0.379		0.041
Very High	539	1081	0.156	0.140	−0.016	−0.053	0.020	0.392		0.053
Extreme	13	25	0.154	0.120	−0.034	−0.266	0.199	0.787		0.362
Parcel rating										
Low	260	543	0.131	0.088	−0.042	−0.090	0.005	0.081		0.068
Moderate	101	209	0.218	0.105	−0.113	−0.204	−0.022	0.017	*	0.131
High	497	1030	0.139	0.135	−0.004	−0.041	0.033	0.837		0.053
Very High	403	826	0.119	0.125	0.006	−0.033	0.044	0.778		0.056
Extreme	231	464	0.091	0.144	0.053	0.004	0.103	0.033		0.070

[A] p value for two-sample t test with unequal variances

[B] Asterisk signifies significant result as determined by Benjamini–Hochberg procedure for controlling for a 10% false discovery rate across the 11 comparisons for Treatment 1

[C] Individually observable effect size at 80% power, based on group sample sizes and observed variances independent, identically distributed error term. Similarly, we estimate the effects of the second treatment also with a logistic regression model of the equation

$$\begin{aligned} y_i = \beta_1 Treatment_i + \beta_2 Community_i + \beta_3 \left(Treatment_i * Community_i\right) \\ + \beta_4 Parcel_i + \beta_5 \left(Treatment_i * Parcel_i\right) + \beta_6 Neighbor_i \\ + \beta_7 \left(Treatment_i * Neighbor_i\right) + \epsilon_i \end{aligned}$$

where now $Treatment_i = 1$ if the letter provided the social comparison information (i.e., Neighbor rating) and $Treatment_i = 0$ otherwise, $Neighbor_i$ corresponds to a set of indicator variables for the Neighbor ratings, and all other variables are defined as above.

3 Results

We present results for the two treatments, personalized Parcel information and the social comparison Neighbor information, separately.

3.1 Treatment 1—personalized parcel information

Table 1 presents the separate response rates and the associated treatment effects for the individual Community rating levels (top panel) and the individual Parcel rating levels (bottom panel). Treatment effects are presented in terms of the percentage point difference from the control group response rate. Significance of differences is explored both with 95% confidence intervals and with standard two-tailed p values for the two-sample t test for each difference between treatment and control. In the final column, we present the minimum observable effect size at 80% power based on the observed variances and the relevant subsample sizes for each comparison's control and treatment groups.

We employ the Benjamini–Hochberg approach to account for multiple comparisons (Benjamini and Hochberg 1995) with a 10% false discovery rate, which controls for as many as one out of ten, otherwise significant results to be false positives. This correction results in rejecting the null hypothesis for the comparisons with the two lowest p values: Community = Low and Parcel = Moderate. Thus, while the overall combined treatment effect is estimated near zero (− 0.007), we find evidence that response rates differ significantly with respect to treatment for two categories. Specifically, for letter recipients in low-risk communities, receiving the Parcel-level risk description in addition to their Community risk rating is associated with an increase in response rate from 0.042 to 0.148, a difference of 0.106. Treatment effects for properties rated moderate represent a decrease in response rate of 0.113. Thus, while we find no evidence that response rates vary significantly with treatment for recipients with most Community or Parcel ratings after adjusting for multiple comparisons, the two significant results provide evidence of a heterogeneous response to treatment as a function of presented information.

To investigate the possibility of Community ratings confounding the treatment effects estimated for Parcel ratings, Table 2 shows the effect of the personalized parcel-level risk information treatment on "Web site" visits using a logistic regression model of response rates, as well as the marginal effects of treatment for the different Community and Parcel rating levels estimated as contrasts of margins, which are robust to nonlinear models such as the logit. Results are similar to those from a linear probability

Table 2 Modeled results for the effect of providing personalized parcel-level risk information (Treatment 1) (logit model, $y=1$ if "Web site" visit)

Dep.Var. $y=1$ if Response, $y=0$ otherwise	Model results			Marginal effect of treatment		
	Coef.	*p* value*	s.e	Mean	95% interval	
Treatment (parcel information)	−0.096	0.541	0.158	−0.005	−0.024	0.014
*Community rating (joint test p value = 0.022)**						
Low	−0.940	0.038	0.452			
Moderate	0.300	0.328	0.307			
High	[baseline]					
Very high	0.343	0.048	0.174			
Extreme	0.340	0.641	0.730			
*Treatment*community rating (joint test p value = 0.038)*						
Treatment*low	1.382	0.002*	0.440	0.105	0.049	0.161
Treatment*moderate	0.096	0.809	0.396	0.006	−0.080	0.093
Treatment*high	[baseline]			−0.013	−0.039	0.013
Treatment*very high	0.069	0.677	0.165	−0.016	−0.038	0.006
Treatment*extreme	−0.107	0.830	0.499	−0.036	−0.165	0.094
Parcel rating (joint test p value = 0.057)						
Low	−0.057	0.782	0.206			
Moderate	0.580	0.083	0.335			
High	[baseline]					
Very High	−0.137	0.567	0.240			
Extreme	−0.362	0.059	0.192			
*Treatment*parcel rating (joint test p value = 0.003)**						
Treatment*low	−0.410	0.135	0.275	−0.040	−0.086	0.006
Treatment*moderate	−0.842	0.013*	0.341	−0.108	−0.206	−0.011
Treatment*high	[baseline]			−0.002	−0.035	0.031
Treatment*very high	0.061	0.809	0.252	0.006	−0.035	0.048
Treatment*extreme	0.477	0.024*	0.211	0.054	0.033	0.075
Constant	−2.021	< 0.001*	0.172			
N	4564					
AIC	3443.139					
p value (chi2)	< 0.001					

Asterisk (*) signifies significant result as determined by Benjamini–Hochberg procedure for controlling for a 10% false discovery rate across the 22 comparisons; coef., coefficient; s.e., standard errors adjusted for 95 experimental blocks

model of response rates estimated via ordinary least squares, which benefits from more direct interpretability but is theoretically inappropriate for a binary response variable; the results of the linear probability model are provided in Table A1 in the "Appendix". We again control for multiple comparisons using the Benjamini–Hochberg procedure with a 10% false discovery rate, this time for the 26 hypotheses tested. Focusing first on the parameters on the non-interacted Community and Parcel ratings, the joint test for Community rating is significant, suggesting that, absent the treatment, individuals in communities with different ratings differ in likelihood of visiting the "Web site", despite none of the specific rating levels being estimated as significant after adjustment for multiple comparisons. This effect underscores the importance of controlling for baseline response rates within a given rating category when estimating treatment effects within that rating category.

We estimate treatment effects for each rating category by estimating the interactions between the treatment and the respective rating categories; marginal effects for these variables provide estimated treatment effects in terms of response rates. Consistent with the simple comparisons from Table 1, treatment effects are positive and significant for properties in low-rated communities and negative and significant for parcels rated moderate. In addition, the logit model also finds a positive and significant effect from treatment for parcels rated extreme. Significant marginal effects demonstrate an average increase in response rate of 0.105 for communities rated low and of 0.054 for parcels rated extreme, and an average decrease of 0.108 for parcels rated moderate, due to treatment. In contrast to the basic t test comparisons, the simultaneous estimation in the logit model demonstrates that the significant treatment effects for Parcel ratings persist even when controlling for Community ratings, and vice versa. That is, the positive effect from treatment on properties in low-risk communities stands regardless of the parcel rating provided in that treatment; likewise, treatment effects from being informed of moderate or extreme parcel ratings do not depend on the community level provided on the letters mailed to members of the control group.

To further investigate whether the effects of receiving the personalized Parcel information arise from that information itself or from the comparison of that information to the (always provided) Community rating, we consider the results of t tests that compare the treatment effect on response rates for combined interactions of Community and Parcel ratings (Table 3). Because we lack sufficient power to investigate the full set of 25 combinations, we collapse the five ratings for Parcel and Community risks into three ratings each. Many of these results are not significant even without accounting for multiple comparisons, yet the approximate magnitudes and directions of estimated effects provide no evidence to suggest that the Parcel-level response to treatment depends on the Community-level rating. Namely, treatment effects for low-/moderate-rated parcels trend toward negative across all Community rating categories, whereas treatment effects for high-rated parcels are ambiguous across all Community ratings, and treatment effects for very high-/extreme-risk parcels are generally estimated as positive or ambiguous for all Community ratings. As such, we find no evidence to suggest that the Parcel rating treatment effect depends on the relative level of that rating versus the Community rating, other than the above-noted large treatment effect for properties with low community ratings, which is found across all Parcel ratings. In addition, reported results for the effects of the first treatment are not significantly changed by the further inclusion of nearest neighbor information or by the exclusion of properties for which neighbor information was provided (see "Appendix" Table a2).

3.2 Treatment 2—social comparison information

Next, we present Table 4, which is formatted similarly to Table 1, but instead shows t tests for the effects of treatment 2 (i.e., the inclusion of social comparison information) across each of the Community, Parcel, and Neighbor rating categories. Strikingly, despite having similar power to treatment 1 (i.e., similar minimum observed effect sizes at 80% power for most rating categories), here we find no significant treatment effects across any of the different rating categories after considering the Benjamini–Hochberg procedure for multiple

Table 3 Effects of personalized information treatment on response rates for properties as a function of the intersection of Community and Parcel ratings

Parcel Rating	Community rating							
	Low/moderate		High		Very high/extreme		All	
Low/Moderate	−0.144**	−0.28 to −0.01	−0.025	−0.08 to 0.03	−0.078*	−0.15 to −0.00	-0.062**	−0.10 to −0.02
	$n = 148$		$n = 498$		$n = 467$		$n = 1113$	
High	−0.055	−0.16 to 0.05	-0.005	−0.06 to 0.05	0.011	−0.05 to 0.07	-0.004	−0.04 to 0.03
	$n = 223$		$n = 618$		$n = 680$		$n = 1525$	
Very High/Extreme	0.100**	0.04 to 0.16	−0.013	−0.06 to 0.03	0.000	−0.06 to 0.06	0.023	−0.01 to 0.05
	$n = 534$		$n = 877$		$n = 507$		$n = 1922$	
All	0.025	−0.02 to 0.07	−0.013	−0.04 to 0.02	−0.017	−0.05 to 0.02	-0.007	−0.03 to 0.01
	$n = 909$		$n = 1997$		$n = 1658$		$n = 4564$	

Each cell shows: the average difference with respect to treatment for properties in each Community and Parcel rating combination; the p value of a two-sample t test comparing treated versus not (**$p < 0.01$ or *$p < 0.05$); the 95% confidence interval of the difference; and the total sample size for the comparison

Table 4 Sample size, response rate, treatment effects, and significance of social comparisons treatment by Community rating levels (top panel), Parcel rating levels (middle panel), and Neighbor rating levels (bottom panel)

	Sample size		Response rate		Treatment effect (percentage point)					
	Control	Treatment	Control	Treatment	Difference	95% interval		*p* value[A]	BH[B]	Effect size[C]
All	1541	1531	0.125	0.122	0.00	−0.03	0.02	0.836		0.033
Community rating										
Low	94	95	0.181	0.116	−0.07	−0.17	0.04	0.210		0.146
Moderate	224	224	0.152	0.138	−0.01	−0.08	0.05	0.688		0.094
High	669	660	0.097	0.102	0.00	−0.03	0.04	0.791		0.046
Very high	541	540	0.139	0.141	0.00	−0.04	0.04	0.920		0.059
Extreme	13	12	0.077	0.167	0.09	−0.17	0.35	0.511		0.401
Parcel rating										
Low	274	269	0.088	0.089	0.00	−0.05	0.05	0.947		0.069
Moderate	106	103	0.104	0.107	0.00	−0.08	0.09	0.944		0.120
High	515	515	0.136	0.134	0.00	−0.04	0.04	0.927		0.060
Very high	413	413	0.128	0.121	−0.01	−0.05	0.04	0.752		0.065
Extreme	233	231	0.146	0.143	0.00	-0.07	0.06	0.925		0.092
Neighbor rating										
Low	91	82	0.077	0.122	0.05	-0.04	0.13	0.323		0.130
Moderate	112	112	0.080	0.161	0.08	0.00	0.17	0.065		0.122
High	770	765	0.125	0.115	−0.01	-0.04	0.02	0.561		0.047
Very high	400	404	0.153	0.121	−0.03	-0.08	0.02	0.198		0.068
Extreme	168	168	0.113	0.131	0.02	-0.05	0.09	0.618		0.101

[A]p value for two-sample t test with unequal variances

[B]Asterisk signifies significant result as determined by Benjamini–Hochberg procedure for controlling for a 10% false discovery rate across the 16 comparisons for Treatment 2

[C]Individually observable effect size at 80% power, based on group sample sizes and observed variances comparisons with a 10% false discovery rate. Even without accounting for multiple comparisons, the strongest treatment effect observed across all comparisons is that for a moderate neighbor rating, which is relatively large at 0.08 but with a p value of only 0.065 and a large 95% confidence interval ranging from 0.00 to 0.17.

However, in contrast to the stability demonstrated for the first treatment, here the results are influenced by holding other rating information constant with the logistic regression model, as shown in Table 5. Notably, joint tests for each set of rating indicators, with or without interactions with the treatment, are not significant, with the exception of the joint test for the interaction of treatment with the Neighbor ratings, which rejects the null hypothesis of no difference at $p=0.008$. Here, the coefficient on the treatment effect for being told of a moderate average Neighbor rating is positive and significant, and similarly, the marginal effect of treatment for that category is also significant and estimated as a positive 0.080. Noting the small sample sizes for both the low and moderate Neighbor ratings (173 and 224, respectively), this significant result, when paired with the relatively large, positive, and quite noisily estimated result for the low Neighbor rating, motivates an ex post collapsing of the low and moderate Neighbor rating categories for further consideration. A t test for this combined category finds a significant ($p=0.039$) effect of a 0.066 increase in response rates with treatment. After controlling for multiple comparisons with a 10% false discovery rate, no other coefficients are estimated as significant except for the constant.

4 Discussion

To summarize, we find that each of the treatments produces a heterogeneous effect that depends on the content of the information provided therein, despite finding no main effects from either of the treatments. Specifically, we find that receiving personalized information about one's parcel-level wildfire risk affects information-seeking behavior differently depending on what that level of wildfire risk is. Response rates are lower when letter recipients with lower-rated ("Moderate") properties are informed of those ratings, but response rates are higher when letter recipients with "Extreme"-rated properties are informed of that rating. While we do not have sufficient power to test the full interactions, our analysis suggests that this result depends not on the relationship of the Parcel rating to the Community rating, but rather is consistent across different Community ratings for a given Parcel rating. This is consistent with results from other contexts, such as public health, where the provision of personalized information itself frequently leads to a small but measurable change in behavior (e.g., Noar et al. 2007; Edwards et al. 2013). Further, such heterogeneous response across property rating levels is consistent with sign reversals (Schultz et al. 2007) and response attenuation (Allcott 2011; Ayres et al. 2013; Brandon et al. 2018) across different levels found in some other contexts.

At the same time, we do find indirect evidence suggesting the comparison might not always be irrelevant, because letter recipients in communities rated as low risk, 85% of whom have a Parcel risk rating that exceeds "Low," are significantly more likely to visit the "Web site" when informed of their Parcel rating. We also find weak evidence of a small social comparisons effect on the one end of the spectrum of Neighbor ratings, in which response rates are higher when letter recipients are informed that their neighbors generally have low- or moderate-rated properties. While speculative, given the ex post decisions

Table 5 Modeled results for the effect of providing social comparison information (Treatment 2) (logit model, $y = 1$ if "Web site" visit)

Dep.Var. $y = 1$ if Response, $y = 0$ otherwise	Model results			Marginal effect of treatment		
	Coef	p value*	Std.Err	Mean	95% interval	
Treatment (neighbor information)	−0.075	0.658	0.169	−0.003	−0.018	0.012
Community rating (joint test p value = 0.050)						
Low	0.702	0.015	0.290			
Moderate	0.403	0.040	0.196			
High	[baseline]					
Very high	0.413	0.033	0.193			
Extreme	−0.267	0.816	1.150			
*Treatment*community rating (joint test p value = 0.635)*						
Treatment*low	−0.554	0.164	0.398	−0.066	−0.154	0.022
Treatment*moderate	−0.034	0.855	0.185	−0.013	−0.046	0.019
Treatment*high	[baseline]			0.004	−0.017	0.026
Treatment*very high	−0.007	0.973	0.192	0.002	−0.025	0.028
Treatment*extreme	0.955	0.438	1.232	0.091	−0.095	0.278
Parcel rating (joint test p value = 0.141)						
Low	−0.382	0.044	0.190			
Moderate	−0.266	0.250	0.231			
High	[baseline]					
Very high	−0.137	0.503	0.205			
Extreme	0.122	0.563	0.211			
*Treatment*parcel rating (joint test p value = 0.952)*						
Treatment*low	−0.171	0.525	0.269	0.001	−0.034	0.037
Treatment*moderate	0.007	0.975	0.216	0.003	−0.031	0.036
Treatment*high	[baseline]			−0.002	−0.028	0.024
Treatment*very high	0.083	0.694	0.211	−0.007	−0.040	0.026
Treatment*extreme	0.040	0.867	0.241	−0.003	−0.040	0.033
Neighbor rating (joint test p value = 0.195)						
Low	−0.397	0.236	0.335			
Moderate	−0.404	0.108	0.251			
High	[baseline]					
Very high	−0.007	0.409	0.192			
Extreme	0.955	0.365	1.232			
*Treatment*neighbor rating (joint test p value = 0.008)**						
Treatment*low	0.729	0.136	0.489	0.046	−0.035	0.127
Treatment*moderate	0.952	0.006*	0.346	0.080	0.013	0.147
Treatment*high	[baseline]			−0.010	−0.027	0.006
Treatment*very high	−0.177	0.045	0.236	−0.031	−0.072	0.010
Treatment*extreme	0.302	0.172	0.221	0.019	−0.003	0.041
Constant	−2.104	< 0.001*	0.221			
N	3072					
AIC	2313.249					
p value (chi2)	< 0.001					

Asterisk (*) signifies significant result as determined by Benjamini–Hochberg procedure for controlling for a 10% false discovery rate across the 38 comparisons; coef., coefficient; s.e., standard errors adjusted for 95 experimental blocks underlying the associated analysis, this latter result is consistent with a positive social comparisons effect at the preferred end of the spectrum that is frequently found in other literature studies (e.g., Allcott 2011; Ferraro and Price 2013), yet we find no overall average effect of the social comparison information treatment.

In short, we find that neither an informational nudge nor a social comparisons nudge changes how many people engage with the wildfire mitigation organization *overall*, but both nudge types can affect *who* engages. Despite the lack of an overall result from either treatment, these results have important implications for local or regional wildfire mitigation organizations seeking to stretch limited resources or to target the most high-risk areas. More generally, while this initial exploration into using behavioral nudges to influence WUI homeowner engagement with wildfire mitigation organizations led to a modest overall response rate of only 13%, these results demonstrate that households at risk from natural hazards attend to the specific information presented in outreach materials and thus suggest promise from future investigations into the topic. Our results suggest that providing personalized or social comparison information will not increase overall engagement but rather can shift who engages. While we cannot here answer policy questions such as whether discouraging low-risk properties is desirable, or if future interventions should be designed to avoid a drop in low-risk property engagement, our experimental results have implications that can depend on such program or policy goals; they suggest that providing personalized parcel-specific information in particular can be an effective strategy for encouraging certain populations to either opt-in or opt-out of following up for more information about risks to their property. For example, combining treatment effects for personalized information with low or moderate parcel ratings suggests a robust decrease in response rate with treatment from 0.155 to 0.093, a decrease of 40%. For a resource-constrained program that prioritizes engagement with the residents of higher-risk properties over the residents of other properties, such an effect could lead to a meaningful reduction in staff time devoted to lower-priority engagements. Conversely, for a program that prioritizes engaging with all residents regardless of their properties' risk levels (perhaps because of equity concerns, the transmission of risk across properties, or the opportunity to engage in ancillary conversations such as about evacuation planning), our experimental results still offer a pathway for optimization and thus increased efficiency, of community outreach. For example, the provision of parcel-level risk information corresponds to an increase in response rates of 5.3 percentage points for parcels rated at extreme risk, which equates to a 58% increase in response versus the baseline response rate of 0.091 for parcels in that same risk category but not informed of their risk. The shift from 0.091 to 0.144 response rate corresponds with a reduction in the average cost per "Web site" visit for extreme-risk parcels from \$33 per visit to \$21 per visit, based on an approximately \$3.00 per address for materials and postage (ignoring other costs, such as staff time and "Web site" development, that are relatively negligible on the margin). Similarly, adding parcel risk information on materials sent to members of a low-risk community could shift the cost per "Web site" visit from a particularly high cost of \$72 per visit (based on a 0.042 response rate) to a more modest cost of \$20 per visit. Thus, for either programmatic goal, our experimental results offer pathways for optimization and thus increased efficiency, in community outreach.

Finally, we have found that tracking behavior change associated with an informational nudge is particularly challenging in natural hazards contexts compared to the contexts of many previous studies, such as those focused on household energy and water use. In the interests of observing a low-cost, yet meaningful behavioral response, here we focus on information-seeking by visiting an informative "Web site". While the ultimate socially beneficial outcome—wildfire risk mitigation—is comprised of many disparate actions, is difficult to observe, and occurs over long time periods, WRWC views information-seeking as an important first step for homeowners to pursue wildfire risk mitigation on their property. Indeed, WRWC observed increased mitigation efforts among households in the sample concurrent with the experiment. For example, one fire protection district went from an average of two sponsored hazardous fuels reduction projects each year to seventeen completed projects in the year of the mailing. While we are unable to connect these more meaningful actions to the treatments investigated, future research inspired by our initial success in observing behavioral responses to small changes in the outreach materials sent to WUI residents about their wildfire risk could apply an experimental approach to deliver additional causal insights into possible interventions for increasing risk mitigation behavior on private property.

To conclude, this study merely scratches the surface of potential applications of behavioral economics interventions for mitigating the risks of natural hazards. Logical next steps include directly assessing whether the observed responses lead to persistent behavioral changes in terms of mitigation and other actions related to improving adaptation to wildfire on the ground, and how these changes relate to different information treatments. Linking to other sources of information, such as social survey data on homeowners' risk perceptions before receiving a nudge letter, could help elucidate mechanisms underlying the different response rates we observe. Given observations of variation across communities in many aspects related to homeowners' relationships with wildfire risk (McCaffrey et al. 2011; Paveglio et al. 2015; Meldrum et al. 2018), we wonder about the extent to which results would hold across different types of communities and other locations, and we hope that future work can utilize larger samples, distributed across more communities, to improve understanding of our results' generalizability and robustness. Finally, wildfire is only one of many natural hazards that threatens society. Given the promise of these initial findings, we hope our work encourages further exploration of the potential of behavioral economics nudges for mitigating risks across the wide spectrum of natural hazards.

Appendix

See Fig. 2.

West Region Wildfire Council

Working Together to Reduce Wildfire Risk

FIRE DEPT

2016 Updated Full Name
2016 Updated Address 1
2016 Updated Address 2

August 8, 2016

Dear Cedaredge Resident,

We have recently seen the devastating effects of wildfire in Colorado communities. We do not want to see homes destroyed by a wildfire in Cedaredge. Therefore, the Cedaredge Volunteer Fire Department and the West Region Wildfire Council (WRWC) are working together to help homeowners reduce their risk from wildfire. We all need to *work together to reduce our risk from wildfire.*

As part of the 2014 Community Wildfire Protection Plan (CWPP), WRWC conducted a wildfire risk analysis in your area to determine how residents can be better prepared in the event of a wildfire. We thought you might be interested in the following information about your wildfire risk:

Your community's overall wildfire risk is rated as:	[Community rating]
Your own property's wildfire risk rating is:	[Parcel rating]
The average wildfire risk rating of your ten closest neighbors:	[Neighbors rating]

LOW	MODERATE	HIGH	VERY HIGH	EXTREME

West Region Wildfire Council is providing you with more information about your property's wildfire risk and what you can do about it. To learn more, you can visit a website built and maintained by WRWC that is specific to your home.

Go to (www.COwildfire.org/myhome) and type in this code when asked: XXXXX

To learn more about programs and funding available to assist you in your efforts to reduce your wildfire risk, please contact Jamie Gomez, Mitigation & Education Coordinator for Delta, Ouray, and San Miguel Counties, at **(970) 615-7300**.

Sincerely,

[signature]

Jamie Gomez
Mitigation & Education Coordinator
West Region Wildfire Council

[signature]

Tom Laird
Fire Chief
Cedaredge Volunteer Fire Department

Fig. 2 Example of the nudge letter mailed to residents of the Cedaredge Fire Protection District who were assigned to Group C, thus displaying Community, Parcel, and Neighbor ratings. [Note: can be printed without color.]

See Tables 6, 7

Table 6 Modeled results for personalized parcel-level risk information (Treatment 1) compared to community-level information (linear probability model, compare to Table 2)

Dep.Var. $y=1$ if Response, $y=0$ otherwise	Model results			Marginal effect of treatment		
	Coef.	*p* value*	s.e	Mean	95% interval	
Treatment (parcel information)	−0.008	0.637	0.017	-0.005	-0.026	0.015
*Community rating (joint test p value = 0.002)**						
Low	−0.057	0.019*	0.024			
Moderate	0.033	0.358	0.035			
High	[baseline]					
Very high	0.039	0.044	0.019			
Extreme	0.039	0.678	0.093			
*Treatment*community Rating (joint test p value = 0.022)**						
Treatment*low	0.104	0.001*	0.031	0.1	0.044	0.155
Treatment*moderate	0.009	0.844	0.047	0.006	−0.082	0.095
Treatment*high	[baseline]			−0.013	−0.041	0.015
Treatment*very high	0.003	0.855	0.019	−0.016	−0.039	0.007
Treatment*extreme	-0.016	0.811	0.068	−0.035	−0.166	0.095
Parcel rating (joint test p value = 0.164)						
Low	−0.007	0.955	0.024			
Moderate	0.082	0.168	0.059			
High	[baseline]					
Very high	−0.015	0.566	0.027			
Extreme	−0.035	0.086	0.02			
*Treatment*parcel rating (joint test p value = 0.008)**						
Treatment*low	−0.039	0.199	0.03	−0.04	−0.09	0.009
Treatment*moderate	−0.11	0.064	0.059	−0.11	−0.222	0.001
Treatment*high	[baseline]			−0.002	−0.037	0.032
Treatment*very high	0.007	0.815	0.028	0.006	−0.036	0.049
Treatment*extreme	0.048	0.048	0.024	0.054	0.03	0.078
Constant	0.118	< 0.001*	0.019			
N	4564					
R^2	0.009					
p value (F test)	< 0.001					

Asterisk (*) signifies significant result as determined by Benjamini–Hochberg procedure for controlling for a 10% false discovery rate across the 22 comparisons; coef., coefficient; s.e., standard errors adjusted for 95 experimental blocks

Table 7 Modeled results for Treatment 1 (logistic regressions, $y=1$ if "Web site" visit) including indicator variables for Neighbor ratings (compare to Table 2); group 3 (with Neighbor ratings shown) omitted due to confounding with Treatment 2

Dep.Var. y = 1 if Response, y = 0 otherwise	Model results			Marginal effect of treatment		
	Coef.	*p* value*	s.e	Mean	95% interval	
Treatment (parcel information)	−0.070	0.725	0.198	−0.005	−0.024	0.015
Community Rating (joint test p value = 0.041)						
Low	−0.931	0.044	0.462			
Moderate	0.292	0.353	0.315			
High	[baseline]					
Very High	0.351	0.053	0.181			
Extreme	0.330	0.652	0.733			
*Treatment*community rating (joint test p value = 0.022)*						
Treatment*low	1.633	0.001*	0.499	0.141	0.060	0.221
Treatment*moderate	0.111	0.785	0.406	0.013	−0.077	0.103
Treatment*high	[baseline]			−0.015	−0.038	0.008
Treatment*very high	0.062	0.729	0.178	−0.017	−0.043	0.009
Treatment*extreme	−0.597	0.450	0.791	−0.076	−0.198	0.046
Parcel rating (joint test p value = 0.170)						
Low	0.017	0.938	0.220			
Moderate	0.589	0.078	0.334			
High	[baseline]					
Very High	-0.151	0.528	0.239			
Extreme	-0.315	0.144	0.215			
*Treatment*Parcel Rating (joint test p value = 0.008)**						
Treatment*low	−0.399	0.122	0.258	−0.042	−0.081	−0.004
Treatment*moderate	−0.856	0.010*	0.330	−0.109	−0.202	−0.017
Treatment*high	[baseline]			−0.002	−0.037	0.033
Treatment*very high	0.014	0.955	0.251	0.009	−0.035	0.054
Treatment*extreme	0.437	0.111	0.274	0.055	0.024	0.086
Neighbor rating (joint test p value = 0.544)						
Low	−0.442	0.196	0.342			
Moderate	0.119	0.550	0.199			
High	[baseline]					
Very High	0.079	0.726	0.226			
Extreme	−0.145	0.638	0.308			
*Treatment*Neighbor Rating (joint test p value = 0.491)*						
Treatment*low	0.045	0.905	0.376	−0.021	−0.073	0.031
Treatment*moderate	−0.523	0.091	0.309	−0.072	−0.123	−0.020
Treatment*high	[baseline]			−0.017	−0.045	0.012
Treatment*very high	0.094	0.692	0.238	0.025	−0.021	0.071
Treatment*extreme	−0.077	0.842	0.386	0.029	−0.017	0.076
Constant	−2.034	< 0.001*	0.203			
N	3033					
AIC	2324.062					
p value (chi2)	< 0.001					

Table 7 (continued)

Asterisk (*) signifies significant result as determined by Benjamini–Hochberg procedure for controlling for a 10% false discovery rate across the 32 comparisons; coef. = coefficient; s.e. = standard errors adjusted for 95 experimental blocks

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Compliance with ethical standards

Conflict of interest The authors declared that they have no conflict of interest.

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