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Do actions speak louder than words? Comparing the effect of risk aversion on objective and self-reported mitigation measures

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ABSTRACT

In this article, we empirically examine whether the relationship between risk aversion and self-reported risk mitigating behavior is similar to the relationship between risk aversion and an objective measure of risk mitigating behavior. Despite higher levels of risk mitigation in the self-reported measure relative to the objective measure, we find risk aversion is similarly correlated with both measures of wildfire risk mitigation. These results provide some confidence in the use of self-reported behaviors in examinations of risk preferences and risky behaviors, even if the self-reports understate objective behavioral measures.

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1. Introduction

Risky behaviors are of public concern when they are associated with negative externalities. Public programs and policy seek to incentivize less risky behaviors in an effort to reduce or eliminate such social costs. It is in this context that the relationship between risk aversion and risky behaviors is of particular interest. However, the literature on risk aversion and risky behaviors has largely relied on self-reported behaviors. Whether intentional or unintentional, self-reported behaviors may differ from objective measures of behavior. Because policies and programs are often based on objective measures of behavior, rather than self-reports, we ask the question of whether observed relationships between risk preferences and self-reported behaviors extend to objective measures of behavior.

Wildfire risk mitigation is a quintessential example where risky behaviors (i.e. failure to mitigate wildfire risk) by private land owners impose substantial social costs. Indeed, development of private land parcels in fire prone areas, along with

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climate change and a history of wildfire suppression, have contributed to the increased devastation associated with wildfires over the last 30 years in western North America (Schoennagel et al., 2017). In the United States, the National Cohesive Wildland Fire Management Strategy provides a vision for the wildfire community toward three goals: 1. Resilient Landscapes; 2. Fire Adapted Communities; and 3. Safe and Effective Wildfire Response (www.forestsandrangelands.gov/strategy/). Homeowner wildfire mitigation and education programs are a key aspect of creating Fire Adapted Communities (www.fireadapted.org). A central effort of such programs is to work with homeowners to improve the survivability of their homes by encouraging the creation of "defensible space" (i.e., an area around a structure that has been maintained and designed to reduce fire danger) and to reduce the likelihood of homes catching fire through the use of ignition-resistant building materials, often referred to as home hardening.

While fire science provides guidance on what needs to be done to reduce the loss of homes from wildfires (Cohen, 2000; Quarles et al., 2010) and studies have established the efficacy of such efforts (Syphard et al., 2014), there are many residents in fire prone areas that do not sufficiently mitigate wildfire risk on their properties. Wildfire risk education programs, as well as building codes and defensible space policies, incentivize wildfire risk mitigation on private land parcels. These programs are often designed based on parcel wildfire risk assessments conducted by a wildfire professional. However, residents may view parcel wildfire risk differently than a professional. We would expect risk preferences to be related to self-assessments of mitigation efforts. However, it is an open question whether professional and self-assessments align and whether the risk preferences of parcel residents are similarly related to self and professional assessments.

Wildfire risk mitigation provides an interesting context to expand the literature on risk preferences and risky behaviors. In this article we use an application in the context of wildfire to test whether the relationship between risk aversion and risk mitigation is similar across self-assessments and professional assessments. As there are very few studies of risk preferences and risky behaviors in the context of wildfire, this study also adds a wildfire application to the literature.

2. Literature

2.1. Measuring risk preferences and risky behaviors

Before considering the literature on the relationship between risk preferences and risky behaviors we summarize a few key findings related to measurement of risk preferences and risky behaviors. Variation in how risk preferences and risky behaviors are measured are likely contributing factors to the disparate results reported in the literature on aversion and risky behaviors summarized below. The most common approach to measure risk aversion, and often considered the gold standard, is to observe choices over a series of real-money lottery questions (Holt and Laury, 2002). This approach and its variants are problematic for general population surveys as the cost of monetary incentives can be prohibitive with large samples and the lotteries may involve sequences of choices too numerous for inclusion in a general survey (Coppola, 2014). Therefore several direct elicitation approaches have been developed. An in-depth review of prevalent approaches to measuring risk preferences concludes "[*i*]n view of the limited predictive power of experimentally-elicited risk preferences across domains, sometimes the advantages of complex methods may well be outweighed by the disadvantage of decreased comprehension, and consequently, producing substantially noisier data. Simpler methods have the advantage of being more straightforward and capable of eliciting sensible risk preferences from a broader set of individuals, but similar care should be taken in extrapolating from these measures to other domains." (Charness et al., 2013, p.50)

Researchers have also examined how risk preferences vary across domains (Weber et al., 2002; Bartczak et al., 2015; Meraner et al., 2018). Weber et al. (2002) found risk preferences to vary across different domains using direct elicitation questions. However, Bartcak et al. (2015) found risk preferences to be similar in financial and environmental (i.e. forest fires) domains using a lottery mechanism to measure risk preferences. Meraner et al. (2018) found that context influences inconsistencies in lottery preference elicitation, however, the correlation coefficients from both lottery contexts considered were similarly correlated with a survey question elicitation of risk preferences.

Studies of risk preferences and risky behaviors largely rely on self-reports of behaviors. However, self-reported behaviors may differ from objective measures of the same behaviors. Inaccuracies in reported behaviors could be intentional if respondents have an incentive to misrepresent risky behaviors or unintentional if cognitive biases or recall difficulties are present. Social desirability bias may result in over-reporting of socially desirable behaviors and underreporting of socially undesirable behaviors (Fisher, 1993). Likewise, recall of behaviors can be cognitively burdensome and result in recall bias (Schwarz, 1990). Validation of self-reported risky behavior is problematic for a number of reasons; most importantly, benchmarks are elusive or very difficult to measure. In the context of wildfire, Meldrum et al. (2015b) found divergences in parcel level wildfire risk characteristics between self-assessments from household surveys and professional assessments from a wildfire specialist.

2.2. Risk preferences and risky behaviors

The literature on risk preferences and risky behavior is vast and disparate. Risk aversion has been found to be both negatively (Tsaneva, 2013) and positively correlated (Hellerstein et al., 2013) with risky behaviors. Incongruent results extend to examinations of risk preferences and risk mitigating behaviors related to natural hazards including wildfire. For example, using a large dataset (4200 observations) of German households, Osberghaus (2015) found a counterintuitive result that, controlling for many other factors, risk seeking individuals reported higher levels of household flood mitigation. Focusing on structural and non-structural (avoidance and emergency preparedness) flood mitigation measures for a sample of households in France, Poussin et al. (2014) found risk aversion to be positively correlated with implementation of structural flood mitigation measures but not with the non-structural flood mitigation measures. Purchase of flood insurance has also been considered in the literature. Botzen and van den Bergh (2012) found risk averse respondents to have a higher willingness to pay for flood insurance in the Netherlands. Conversely, Raschky et al. (2013) did not find risk aversion to be related to willingness to pay for flood insurance for a sample of households in Austria and Germany. However, they did find risk averse respondents were more likely to report actual purchases of flood insurance. Petrolia et al. (2013) found that risk aversion and subjective perceptions of risk, in addition to objective measures of risk, were positively related to the likelihood of purchasing flood insurance. In a similar study that examined the joint decision to purchase wind insurance and undertake flood risk mitigation measures, Petrolia et al. (2015) found that risk aversion had a positive, marginally significant (at 10% level) effect on the flood insurance decision but no effect on the number of mitigation measures completed.

In the context of wildfire, Holmes et al. (2013) found that study participants' willingness to pay for reducing wildfire exposure was less than the expected loss without the program under consideration. In other words, participants were found to be risk seeking. Likewise, Prante et al. (2011) used laboratory experiments to examine policy tools to incentivize mitigation of wildfire risk on private property. They found risk averse participants spent fewer lab dollars on mitigation, were less likely to mitigate, and spent fewer lab dollars on mitigation and insurance together.

In the context of fire managers evaluating the costs and benefits of hypothetical wildfire suppression scenarios, risk preferences were found to be an important factor (Wibbenmeyer et al., 2013; Hand et al., 2015). Hand et al. (2015) found the risk averse fire managers made decisions that departed from loss minimization with respect to expenditures, property damages, or risk of fire fighter fatalities.

To summarize, the nature of the relationship between risk preferences and risky behaviors remains inconclusive. Narrowing in on a natural hazards context similar to wildfire, studies of risk preferences and flood mitigation behaviors have also produced disparate results. In the context of wildfire, risk aversion has been found to be positively correlated with risky behaviors. Specifically, participants in a wildfire protection choice experiment were found to be risk seeking; risk averse participants in a laboratory experiment spent less on mitigation and insurance; and risk aversion of fire managers was found to be associated with decisions that did not minimize costs of suppressing fires.

2.3. Wildfire risk mitigation

While the focus of this study is on risk aversion and wildfire risk mitigation on private land parcels, the sizeable literature on wildfire risk mitigation suggests there are other factors related to risk mitigating behaviors that should also be considered. The studies of wildfire risk mitigation decisions have examined many potential correlates. The relationship between wildfire risk perceptions and risk mitigating behaviors has been examined in several studies (Martin et al., 2007; McCaffrey et al., 2011; Collins 2009; Gordon et al., 2012; McNeill et al., 2013; Brenkert-Smith et al., 2012). Examinations of social factors and wildfire risk mitigation have provided mixed findings. Informal social interactions such as talking with a neighbor about wildfire has been found to be positively correlated with wildfire risk mitigation behaviors (Dickinson et al., 2015). In contrast McCaffrey et al. (2011) failed to find relationships among community members to be related to mitigation outcomes. Firsthand experience with wildfire such as being evacuated has also been examined in relationship to wildfire risk mitigation with mixed results. Some studies failed to find a statistically significant correlation (Martin et al., 2009; Schulte and Miller, 2010) while Brenkert-Smith et al. (2012) found a strong positive correlation.

3. Conceptual wildfire risk mitigation model

We develop a conceptual model similar to that of Petrolia et al. (2015) in which decisions to mitigate and insure against wind damage are jointly determined and depend on perceived likelihood of a storm. We adapt that general framework with a focus on decisions to mitigate wildfire damages. Faced with perceived probability p_i that a wildfire will reach its property, household i chooses whether or not to undertake any combination of N possible mitigation actions to reduce expected damages from wildfire. Let the expected utility of household i be $EU(H_i, X_i, m_{i1}, .., m_{iN}|p_i, r_i, w_i, Z_i)$ where H_i is consumption of housing, $X_i$is consumption of a numeraire good, m_{i1}, .., m_{iN} are mitigation levels, r_i is the level of risk aversion, w_i is wealth, and Z_i is a vector of personal characteristics likely to affect demand for mitigation. Inclusion of the Z variables is guided by previous models of wildfire risk and the associated literature. Based on the wildfire risk mitigation literature, we consider perceptions of neighbors' vegetation, informal social interactions, length of residency, income, county of residence, and expectations about the fire department saving the home. Assuming well-behaved underlying utility functions, the first order conditions for the utility maximization problem implicitly define a set of demand functions for mitigation,

$$m_{in} = m(p_i, r_i, w_i, Z_i) \quad \text{for} \quad n = \{1, .., N\}$$

We consider two wildfire risk mitigation actions: creation of defensible space and use of building materials that reduce home ignitability (i.e., home hardening). Defensible space is the area around the home that is designed to reduce the risk of a wildfire reaching the structure and provides a safe place for firefighters to defend the home. Clearing dense vegetation and removing combustibles around the home are two actions that a homeowner can take to create defensible space. Homeowners can harden their home by installing a noncombustible roof, using noncombustible siding, and avoiding a combustible attachments such as balconies, decks, fences, and porches.

It is likely that the level of one mitigation action is dependent on the level of the other. For example, households that are more fire-aware likely both actively maintain the vegetation around their home and choose housing materials that are less ignitable. Alternatively, if mitigation actions compete for household expenditures, a household that spends a lot of money on a roof may not have remaining funds to clear vegetation. The joint determination of risk mitigation activities needs to be considered, because failure to consider simultaneity in estimation may result in biased coefficients, (Wooldridge 2006) and in turn, incorrect inference about the relationship between the dependent and independent variables. Any two mitigation activities $(m_1;\ m_2)$ can be described by the following equations:

$$m_1 = X_1\beta_1 + \boldsymbol{\varepsilon}_1$$

$$m_2 = X_2\beta_2 + \boldsymbol{\varepsilon}_2$$

where β_1 and β_2 are parameter vectors; X_1 and X_2 are vectors of explanatory variables; and ε_1 and ε_2 are error terms, assumed to be jointly normal with correlation coefficient ρ and uncorrelated with all covariates in the model. If ρ is insignificant, we would estimate separate models and conclude the two mitigation actions of interest are not jointly determined.

4. Data

The data come from select communities in five counties located on the western slope of the Rocky Mountains in Colorado, USA (see Fig. 1). West Region Wildfire Council and Wildfire Adapted Partnership (formerly known as FireWise of

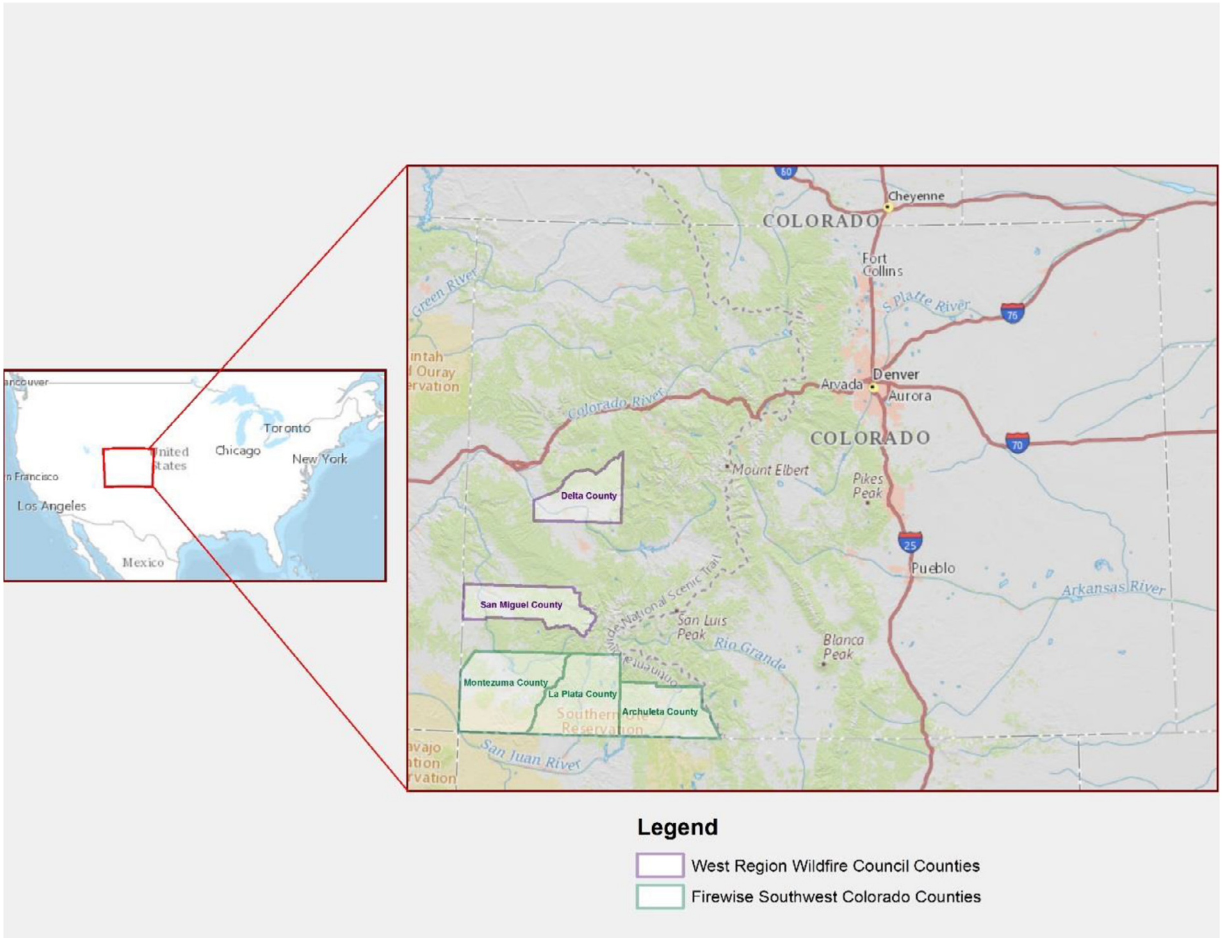

Fig. 1. Location of study counties.

Table 1
Distribution of overall wildfire risk ratings for study population and survey respondents by county.

	Low	Moderate	High	Very High	Extreme
Archuleta County:					
Study Population (n = 702)	2.42%	2.56%	25.93%	41.74%	27.35%
Survey Respondents (n = 200)	3.50%	2.00%	29.00%	39.00%	26.50%
Delta County:					
Study Population (n = 1903)	29.32%	10.30%	38.73%	14.71%	6.94%
Survey Respondents (n = 647)	29.21%	9.89%	38.64%	14.99%	7.26%
La Plata County:					
Study Population (n = 913)	0.33%	0.55%	13.91%	53.12%	32.09%
Survey Respondents (n = 334)	0.30%	0.60%	16.77%	53.29%	29.04%
Montezuma County:					
Study Population (n = 463)	7.78%	7.13%	39.52%	31.32%	14.25%
Survey Respondents (n = 180)	9.44%	8.33%	42.78%	28.89%	10.56%
San Miguel County:					
Study Population (n = 1926)	6.23%	2.39%	18.95%	43.46%	28.97%
Survey Respondents (n = 633)	5.85%	2.53%	19.12%	43.92%	28.59%

Southwest Colorado), two nonprofit organizations that encourage wildfire risk mitigation on private property in western Colorado, operate within the five study counties. The emphasis of both programs is on encouraging community residents to create defensible space near their homes and to reduce the ignitability of the structures. The data were collected in areas identified as having relatively high wildfire risk in each of the counties. West Region Wildfire Council and Wildfire Adapted Partnership followed the same systematic data collection procedures in all counties, developed by a Bureau of Land Management Fire Mitigation Specialist and collaborators over a series of implementations and based on the Home Ignition Zone concept (Cohen, 2000). The general concept is that wildfire risk is assessed within three zones of the home. Zone 1 is the area closest to the home (0–30 feet) and requires the most hazard mitigation to increase the survivability of a home during a wildfire event. Zone 1 is often split into two areas – immediate and intermediate (www.nfpa.org). The immediate zone is very close to the structure (less than 10 feet in the assessment used in this study) while the intermediate zone is ten to thirty feet from the home. Zone 2 (30–150 feet) is further from the home. Mitigation in zone 2 is designed to reduce the intensity of a wildfire approaching the home. Zone 3 (greater than 150 feet) is furthest from the home and may be neighboring property if the lot is small. A related concept is “hardening” of the structure. During a wildfire, ember showers or a flame front can ignite homes if the building materials are combustible. While there are many details to fully “hardening” a home, it starts with noncombustible building materials (roof, siding, and attachments). Based largely on the concepts of defensible space and home hardening, the first step in the data collection protocol was to have a wildfire professional assess eleven attributes on every residential parcel with a home in select communities. The attributes were weighted to provide an overall wildfire risk score that varied from 25 to 665 points and assigned to one of five risk categories from low to extreme (See Appendix A for the risk assessment attributes and weights). The attributes and weights were developed based not only on structure vulnerability during a wildfire event but also considerations such as firefighter access and evacuation potential. The most heavily weighted attributes are roofing material (200 points for a wood roof) and the lack of defensible space (100 points if dense or unmanaged flammable vegetation is less than 10 feet and 75 points if less than 30 feet from the home). By design, these ratings reflect a property’s risk relative to the overall level of risk within its community rather than an absolute risk rating. The assessments were conducted from the road and designed to take a few minutes per parcel.

In a companion effort, the wildfire councils implemented a household mail survey of the properties that the wildfire specialist had assessed for wildfire risk (details of the survey data collection effort for each county are described in Meldrum et al., 2015a; Meldrum et al., 2017; (Meldrum et al., 2017) Meldrum et al., 2019a; Meldrum et al., 2019b; Brenkert-Smith et al., 2019). Survey questions were designed to mirror the attributes on the professional assessment. The study population included all of the parcels with a completed risk assessment. Because we have the professional risk assessments for all of the properties in the study population, we are able to compare the parcel risk assessments for survey respondents to the study population. This serves as a check of nonresponse bias with respect to the overall parcel level risk variable. The results are described in Table 1. The distribution of wildfire risk ratings for the study population and the survey respondents are similar for each county. The distributions of overall wildfire risk ratings vary across the counties. For example, in La Plata County, 32% of the professionally assessed parcels were rated as extreme. By contrast, only 7% of professionally assessed parcels were rated as extreme in Delta County. Variation in the risk assessments across the counties are partially attributable to differences in natural vegetation, topography, and the home construction/design standards.

The survey contained seven sections that collected information about respondents’ housing, experience with wildfire, wildfire risk perceptions, social interactions, risk preferences, and demographic characteristics. The survey also asked residents to assess their property based on the same parcel level wildfire risk attributes as those assessed by the wildfire specialist. It is important to note that the professional assessment drove the development of the survey questions. We wanted them to be as similar as possible. If one were to just conduct a survey, the risk assessment questions could be simplified. While we refer to the professional assessment as the “objective” measure, we do not necessarily assume that the professional assessment is more accurate than the self-assessment in every case. Given the professionals have training in wildfire

Table 2
Summary statistics for dependent variables (n = 1404).

Variable	Values	Description	Distribution	
			Self[1,2]	Professional[1]
Defensible Space[2]	0 = Low level of defensible space	Dense vegetation less than 10 feet from home; or dense vegetation 30–150 feet from home and other combustibles within 10 feet of home.	12%	38%
	1 = Medium level of defensible space	Dense vegetation 30–150 feet of home and no other combustibles within 30 feet of home; or dense vegetation 10–30 feet from home and no other combustibles within 10 feet of home.	41%	40%
	2 = High level of defensible space	No dense vegetation within 30 feet of home and no other combustibles within 10 feet of home.	33%	15%
	3 = Very high level of defensible space	Dense vegetation more than 150 feet from home and no other combustibles within 30 feet of home.	15%	6%
Mean (Std. Dev.)			2.508 (0.888)	1.887 (0.871)
Home hardening[2]	0 = Low level of home hardening	Wood roof; or noncombustible roof with wood/vinyl siding; or noncombustible roof with an attached deck	53%	60%
	1 = Medium level of home hardening	Noncombustible roof with log/heavy timber siding; or noncombustible roof with log/heavy timber siding and an attached deck; or noncombustible roof with wood/vinyl siding and no deck.	44%	33%
	2 = High level of home hardening	Noncombustible roof with noncombustible or log/heavy timber siding and no deck.	3%	7%
Mean (Std. Dev.)			1.501 (0.557)	1.474 (0.624)

[1] Contingency table analyses reject the null hypotheses that the distributions for the self-assessment and professional assessment defensible space and home hardening variables are independent. For defensible space, Pearsons χ^2 = 88.398; p = 0.000. For home hardening, Pearsons χ^2 = 285.203; p = 0.000.
[2] Contingency table analyses reject the null hypotheses that the distributions for the defensible space and home hardening variables are independent. For self-assessment data, Pearsons χ^2 = 14.999; p = 0.020. For professional assessment data, Pearsons χ^2 = 88.048; p = 0.000.

risk assessments, it is likely that their assessments are, on average, more accurate than the self-assessments. In addition, we expect them to be more precise because the same professional conducted all assessments, using the same criteria, for all properties within a county, whereas each individual survey respondent conducted their own self-reported ratings. However, the professional assessments are a quick look at a property from the road and errors are inevitable. Regardless, the comparisons between the professional assessments and the surveys are notable because residents make decisions based on how they view their parcels (the self-assessment) and the professionals implement community programs based on how they see residents' parcels.

4.1. Risk mitigation measures

We focus our attention on two risk mitigation measures: defensible space and home hardening (see Table 2 for variable descriptions and summary statistics). These variables are composites of a subset of the assessment variables (Appendix A). The defensible space variable includes measures of vegetation and combustibles in the zones near the home. There are four levels of defensible space: low, medium, high, and very high. The professional assessment categorizes many more parcels as having a low level of defensible space (38%) compared to the self-assessment (12%). A similar pattern is evident for home hardening, with the professional assessment reporting 60% of the structures as having a low level of home hardening compared to 53% in the self-reports. While levels of defensible space and home hardening are on average higher in the self-assessment relative to the professional assessment, contingency table analyses suggest they are not independent of each other (Table 2, footnote 1). When we examined the relationships between the defensible space and home hardening variables, contingency table analyses of both the self-assessment and the professional assessment suggest defensible space and home hardening are not independent of each other (Table 2, footnote 2).

4.2. Independent variables

The independent variable of central interest is risk aversion. Table 3 includes the exact wording of the survey question as well as the distribution of response. We see that the distribution of response is slightly skewed to the lower end (not at all willing to take risks) of the 11-point scale. This is reflected in the mean value of 4.591 and a median between 4 and 5 on the 11-point scale. As the risk aversion variable is categorical, we cannot directly include it in the multivariate risk mitigation models and a series of 10 dummy variables is unwieldy. Therefore, we create a dummy variable (1 = risk averse; 0 = other) where the lower quintile is categorized as risk averse and the rest as risk neutral/taking (Table 4). While any approach to transforming the risk preference variable is admittedly ad hoc, we chose a conservative approach to defining risk averse (the lower quintile) and provide the estimated coefficients from other possible re-coding schemes in Table B.1, Appendix B.

The other independent variables for the multivariate models were chosen following wildfire mitigation models in the literature. Table 4 provides descriptions and summary statistics for all the independent variables. We do not have an a

Table 3
Distribution of response to risk averse question.

Do you view yourself as someone who is fully prepared to take risks, or do you try to avoid taking risks?	
0 = not at all willing to take risks	3.99%
1	6.05%
2	10.90%
3	13.89%
4	9.47%
5	24.00%
6	9.69%
7	10.26%
8	6.77%
9	2.21%
10 = very willing to take risks	2.78%
Total	100%
$N = 1404$	
Mean = 4.591; Std. Dev. = 2.366	

Table 4
Summary statistics for independent variables ($n = 1404$).

Variable (original survey values)	Values used in analyses	Mean (Std. Dev.)
Risk Averse (0 = not at all willing to take risks to 10 = very willing to take risks)	1 = 0–2 0 = otherwise	0.209 (0.407)
Chance of a wildfire on property (0 = no chance to 100 = for sure)	0–1	0.188 (0.161)
Dense vegetation on neighbors' properties (1 = very sparse to 5 = very dense)	1 = 4 or 5 0 = otherwise	0.371 (0.483)
Talked to a neighbor about wildfire	1 = yes 0 = otherwise	0.548 (0.499)
Ever evacuated due to a wildfire	1 = yes 0 = no	0.064 (0.246)
Likely the fire department will save home if wildfire (1 = not likely; 5 = very likely)	1 = 4 or 5 0 = otherwise	0.570 (0.495)
Number of years in current residence	Years	16.761 (10.921)
Natural log of annual income (income min = $7480; max = $250,196)	ln(dollars)	11.344 (0.841)
Archuleta	1 = Archuleta 0 = otherwise	0.112 (0.316)
Delta	1 = Delta 0 = otherwise	0.313 (0.464)
Montezuma	1 = Montezuma 0 = otherwise	0.088 (0.284)
SanMiguel	1 = SanMiguel 0 = otherwise	0.313 (0.464)
LaPlata	1 = LaPlata 0 = otherwise	0.172 (0 0.3778)

priori expectation on the sign of the chance of a wildfire on property variable. It is possible that individuals who perceive a higher chance of a wildfire on their property take more action to reduce the risk of losing their home. However, it is also plausible that individuals perceive a higher chance of a wildfire on property because they have not mitigated. The survey question asked about the chance that a wildfire will start on or spread to your property **this year** because current levels of defensible space and the ignitability of a structure would mostly likely be related to imminent risk. In this study population, we see that on average respondents did not think it too likely (19% chance) that their property would be threatened by a wildfire fire in the next year. We explored whether risk averse individuals perceive greater chance of a wildfire on property and did not find the two measures to be related (Pearson $\chi 2 = 9.0195$; $p = 0.435$).

The literature on wildfire mitigation has found that the physical conditions on neighboring properties and the social connectedness to neighbors can be correlated with wildfire risk mitigation. In this study population, we see that 37% of respondents rated most neighboring properties' vegetation as 4 or 5 on a 5-point scale with 5 labeled as 'very dense'. Since wildfire does not respect property ownership boundaries, there are risk spillovers (Butry and Donovan, 2008; Warziniack et al., 2018). As noted in the literature review, previous research has found talking with neighbors about wildfire risk had a positive correlation with reported mitigation behavior (Brenkert-Smith et al., 2012). More than half of the survey respondents (55%) reported talking with a neighbor about wildfire. Previous wildfire experience in the form of evacuation reflects first hand wildfire experience. Evacuations were minimal (6%) in this study population. A variable related to fire response by the local fire department was included in the mitigation models. A popular belief about WUI residents and efforts to

Table 5
Contingency Table Analyses Results (n = 1404).

		Self-Assessment		Professional Assessment	
		Risk Averse	Risk Neutral/Taking	Risk Averse	Risk Neutral/Taking
Defensible Space	0 = Low level of defensible space	9%	13%	12%	38%
	1 = Medium level of defensible space	31%	43%	41%	40%
	2 = High level of defensible space	41%	30%	33%	15%
	3 = Very high level of defensible space	19%	14%	15%	6%
Total		100%	100%	100%	100%
		$\chi^2 = 23.571$ ($p = 0.000$)		$\chi^2 = 21.825$ ($p = 0.000$)	
Home hardening	0 = Low level of home hardening	53%	53%	59%	60%
	1 = Medium level of home hardening	44%	44%	32%	34%
	2 = High level of home hardening	3%	3%	9%	6%
Total		100%	100%	100%	100%
		$\chi^2 = 0.111$ ($p = 0.946$)		$\chi^2 = 2.109$ ($p = 0.348$)	

reduce wildfire risk exposure is that they do not take action to reduce risk because they expect the fire department will save their home. (e.g., moral hazard). However, it is also possible that residents with good defensible space recognize that they made it safer for firefighters to defend their home and the surrounding area. The majority (57%) of the survey respondents reported that it was likely the fire department would save their homes. Characteristics such as length of residency and income are also hypothesized to correlate with mitigation. The average length of residency was found to be approximately 17 years. We created dummy variables for the different counties. While the counties are in the same geographic area, there are differences in the physical and social characteristics across the counties.

5. Results

We first examine the relationship between risk aversion and risk mitigation with simple contingency table analysis. We separately consider the relationship between risk aversion and self-assessment defensible space, professional assessment defensible space, self-assessment home hardening, and professional assessment home hardening for a total of four separate contingency tables (Table 5). The distribution of risk aversion is correlated with the distribution of defensible space for both the self and professional assessment data but not with home hardening for either assessment. We see that risk averse respondents are more likely to have high or very high levels of defensible space compared to risk neutral/seeking respondents for both the self and professional assessments.

The conceptual wildfire risk mitigation model in Section 3 posits the possibility of joint determination of the two mitigation behaviors of interest: defensible space and home hardening. As noted above, contingency table analyses support the possibility of joint determination as the defensible space and home hardening variables were not found to be independent (Table 2). Therefore, we estimate bivariate ordered probit models to accommodate the ordered dependent variables and the possible joint determination of creating defensible space and hardening of the home. We estimate two models: one using the self-assessment data and the other using the professional assessment data for the dependent variables. We also test for heteroscedasticity in the models.

Table 6 provides the results from the empirical models. Model 1 uses the self-assessment data for the dependent variables; Model 2 uses the professional assessment data. Based on tests with full covariate models we did not find evidence of heteroscedasticity. For all the dependent variables, the responses are ordered such that a higher response category reflects a higher level of wildfire risk mitigation. Consistent with the results of the contingency table analyses in Table 2, defensible space and home hardening are found to be jointly determined in the multivariate models.

Critically, the risk averse coefficient is significant, positive, and of similar magnitude in the defensible space equations for Models 1 and 2. Risk averse individuals have higher levels of defensible space, a result that holds for both the self and professional assessment models. The risk averse variable is not correlated with home hardening in either model. These results are consistent with the contingency table analyses reported in Table 5. This result could reflect the expense and difficulty of hardening a home as well as the stronger programmatic focus on creating defensible space.

There are some other consistent findings in the defensible space equations for both Models 1 and 2. In both models, the respondents' perceptions of the chances of a wildfire on their properties was negatively correlated with both self and professional assessments of defensible space. In other words, individuals who perceive a high chance that a wildfire will be on their property have a lower level of defensible space. This result supports the notion that individuals with less defensible space recognize the increased chances of a fire on their properties. Another consistent result between Models 1 and 2 is that individuals that report dense vegetation on neighboring parcels have lower levels of defensible space. While we cannot attribute causation, the intuition of these results could be that individuals are less likely to create defensible space if their neighbors fail to mitigate and they think it inevitable that a fire will start or spread on their property. The third consistent result between the defensible space equations in both models is that long term residents have lower levels of defensible space.

Table 6
Results of bivariate ordered probit regression models.

	Defensible space		Home hardening	
	Coef.	S.E.	Coef.	S.E.
Model 1: Self-assessment dependent variables (n = =1404)				
Risk Averse	0.247 ***	0.071	−0.064	0.080
Chance of a wildfire on property	−0.766***	0.191	−0.143	0.214
Dense vegetation on neighbors' properties	−0.205***	0.062	−0.048	0.069
Talked to a neighbor about wildfire	0.145**	0.062	0.286***	0.070
Ever evacuated due to a wildfire	0.013	0.132	−0.143	0.137
Likely the fire department will save home if wildfire	0.204***	0.062	−0.073	0.067
Number of years in current residence	−0.004**	0.003	0.001	0.003
Natural log of annual income	0.079**	0.039	0.154***	0.044
Archuleta	0.077	0.113	0.154	0.127
Delta	0.123	0.093	0.278***	0.105
Montezuma	0.287**	0.120	0.593***	0.133
SanMiguel	−0.279***	0.093	−0.293***	0.106
ρ = 0.065				
χ^2 *test statistic for independent equations = 3.54; p = =0.060*				
Model 2: Professional assessment dependent variables (n = =1404)				
Risk Averse	0.262***	0.074	−0.038	0.081
Chance of a wildfire on property	−0.402**	0.202	−0.149	0.214
Dense vegetation on neighbors' properties	−0.222***	0.066	0.016	0.070
Talked to a neighbor about wildfire	0.016	0.064	0.059	0.070
Ever evacuated due to a wildfire	−0.022	0.133	−0.244*	0.137
Likely the fire department will save home if wildfire	0.067	0.062	−0.041	0.068
Number of years in current residence	−0.006**	0.003	0.002	0.003
Natural log of annual income	0.057	0.041	0.074	0.044
Archuleta	1.033***	0.127	0.226*	0.133
Delta	1.471***	0.111	0.937***	0.110
Montezuma	1.530***	0.134	1.016***	0.134
SanMiguel	1.187***	0.109	−0.056	0.113
ρ = 0.222				
χ^2 *test statistic for independent equations = 28.80; p = =0.000*				

*, **, *** denote 10%, 5%, 1% significance levels, respectively.
Tests of heteroscedasticity with all covariates (AIC):

Model 1	5681
hetero Model 1	5700
Model 2	5320
hetero Model 2	5262.

The home hardening equations for both models are quite different from the defensible space equations. Other than similar fixed effects for Archuleta, Delta and Montezuma Counties, the two home hardening equation results do not show any similar statistically significant correlates. Likewise, the defensible space and home hardening equations for Model 2 do not have similar significant correlates beyond the county fixed effects. However, consideration of Model 1 shows two consistent results across the defensible space and the home hardening equations. The first is that talking with a neighbor about wildfire is positively correlated with both higher levels of defensible space and higher levels of home hardening. The second result is that income is also positively correlated with both higher levels of defensible space and higher levels of home hardening. Neither of these results extend to Model 2.

Finally, a significant result found only in the defensible space equation in Model 1 is that those who said it is likely the fire department will save their home during a wildfire event, reported a higher level of defensible space.

6. Conclusions

In this study we extended the literature on risk preferences and risky behaviors by comparing how risk aversion is related to a self-reported and an objective measure of behavior. We argue that because policies and programs are often based on objective measures of behavior, rather than self-reports, it is important to understand whether observed relationships between risk preferences and self-reported behaviors extend to objective measures of behavior. Specifically, we looked at the relationship between risk preferences and wildfire risk mitigating behaviors using both self and professional assessments of wildfire risk on private land parcels. As noted earlier, the key result is that the risk averse coefficient is significant, positive, and of similar magnitude in the defensible space equations for both the self-assessment and the professional assessment models. Risk averse individuals have higher levels of defensible space. However, the risk averse variable is not correlated with home hardening in either model. While the self-assessments of both defensible space and home hardening levels were higher than the professional assessments, they were not found to be independent of each other. These results provide some confidence in the use of self-reported behaviors in examinations of risk preferences and risky behaviors, even if the self-reports overstate objective behavioral measures.

As usual, there are a few caveats to this study. The “objective” measure of defensible space and home hardening was collected by a fire professional from the road and was designed to take a few minutes per parcel. A more accurate measure of resident wildfire risk mitigation might include an onsite visit by the professional or images from a drone flying over the property or other imaging data. However, programs and policies probably will not use these refined data sources for assessing every parcel in a community unless they become more cost effective. Future studies should consider creative ways to collect objective measures of behavior.

Another caveat is that the risk preference question used in this study asked about general risks. The literature on risk preferences and risky behaviors has largely found that risk preferences in a specific domain are most strongly related to risk exposure in that same domain. For example, willingness to take risks related to finances have been found to be most closely related to owing individual stocks (Dohmen et al., 2011). However, as mentioned in the literature review, Bartczak et al. (2015) found risk preferences over financial and environmental domains to be similar. The survey used for this study did not ask specifically about willing to take risks related to wildfire. That would be a reasonable avenue for investigation in future studies. Another caveat is that question was used in this study elicited risk preferences on an eleven point ordinal scale from not all willing to take risks to very willing to take risks. While this question is widely used, identification of “risk averse” respondents is admittedly somewhat ad hoc. The coefficient estimates for the risk-averse variable under different re-coding schemes are provided in Table B.1, Appendix B. The result that risk aversion is not correlated to home hardening holds up under all of the re-coding schemes shown in Table B.1, Appendix B. Likewise the result that risk aversion is significantly correlated to both self and professional assessments of defensible space.

Considering the results of this application in the light of previous work, it is interesting to note that in the context of flood mitigation, Poussin et al. (2014) found the opposite result. They found risk aversion to be positively correlated with implementation of structural flood mitigation measures but not with the non-structural flood mitigation measures. These contradictory results highlight the need for caution in generalizing across natural hazards. In the context of wildfire, this study contributes an application with residents in fire prone areas that are involved with decision making regarding wildfire risk mitigation. In contrast to previous wildfire studies, our finding that risk averse respondents have better defensible space is promising. Other studies on risk preferences in the context of wildfire (Prante et al., 2011; Wibbenmeyer et al., 2013; Hand et al., 2015) found risk aversion to be associated with suboptimal decision making. Further, a previous study on risk preferences in the context of wildfire found residents to be risk taking in the context of wildfire (Holmes et al., 2013). While the risk preference measure in this study related to general risk, the risk preferences were skewed toward the risk averse end of the scale. We cannot speculate whether risk preferences would be similar if the survey had asked about willingness to take risks in the wildfire domain.

We wonder how risk preferences and in turn wildfire risk mitigation behaviors might be affected by a future with increased frequency and intensity of wildfires (Moritz et al., 2014). Empirical studies have found risk preferences can be altered by traumatic events, including natural disasters (Eckel et al., 2009; Cameron and Shah, 2015). Indeed, Hanaoka et al., 2018 found that men exposed to the higher intensities of the Great East Japan Earthquake in 2011 became more risk tolerant. Likewise, Kahsay and Osberghaus (2017) found that households were more risk-seeking after direct experience with financial and health related storm damage. If households become more risk tolerant with future wildfires, community wildfire mitigation and education professionals will face unprecedented challenges. Our study population had little firsthand experience with wildfire as only 6% had ever been evacuated due to a wildfire. Study populations exposed to repeated wildfires could also provide different results.

We also found that talking with neighbors about wildfire was positively correlated with defensible space and a less ignitable structure. In this study population, most (55%) people said they had talked with a neighbor about wildfire. However, many (45%) had not. Furthermore, the individuals that reported neighbors with dense vegetation had less defensible space themselves. Perhaps this reflects a positive spillover effect. Programs may want to focus on groups of neighbors to foster informal social interactions around the wildfire issue and leverage positive spillover effects. In addition, programs can emphasize that greater defensible space can improve the chances that the fire department can safely be on a property during a wildfire event.

Moral hazard is of concern if government programs or policies unintentionally discourage mitigating behaviors. Moral hazard associated with structure protection provided by the local fire department was not found to be an issue in this study. Individuals who thought it likely that the fire department would save their home reported better defensible space. Fire departments often communicate that they cannot save homes without defensible space. We do not know the extent to which this policy was communicated in the study area or that fire department response does not discourage parcel mitigation in other areas of the Western USA. Some types of post flood disaster grants have been found to discourage purchases of flood insurance (Kousky et al., 2018; Davlasheridze and Miao, 2019). As home losses related to wildfires continue to rise, examinations of government programs potentially crowding out parcel wildfire mitigation efforts would be very useful.

Do actions speak louder than words? In this study we found that words are actually a reasonable representation of action. When comparing the effect of risk aversion on objective and self-reported mitigation measures, the results of this study suggest a similar relationship that persists when important covariates are also considered. While this one study does not settle the discourse on risk aversion and risky behaviors, it provides additional insights and an application in the context of wildfire, a topic that is currently of great policy and programmatic interest in many parts of the world.

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Appendix A

WRWC's Rapid Wildfire Risk Assessment

25-150	LOW
151-175	MODERATE
176-270	HIGH
271-365	V. HIGH
366-665	EXTREME

ACCESS

Structure address posted at driveway entrance?

	Posted and reflective	0
	Posted, NOT reflective	5
	Not Visible from road	15

Ingress and egress

	Two or more roads in/out	0
	One road in/out	10

Width of driveway

	Greater than 24 feet wide	0
	Between 20-24 feet wide	5
	Less than 20 feet wide	10

STRUCTURE

Roofing material

	Tile, metal, asphalt	0
	Wood (shake shingle)	200

Building exterior

	Non-combustible siding (stucco,	0
	Log, heavy timbers	20
	Wood, vinyl, or wood shake	60

Location of woodpiles and combustibles (light flashy veg., shrubs, trees, trash)

	None or > 30 ft from structure	0
	10-30 feet from structure	10
	< 10 feet from structure	30

Balcony, deck, or porch

	None	0
	Non-Combustible Deck/Fence attached to Structure	20
	Combustible Deck/Fence attached to Structure	50

VEGETATION & TOPOGRAPHY

Slope

	Less than 20%	0
	Between 20% and 45%	20
	Greater than 45%	40

Distance to dangerous topography

	More than 150 feet	0
	50-150 feet	30
	Less than 50 feet	75

Predominant background fuel type in neighborhood

	Light (grasses, forbs, tundra)	25
	Moderate (light brush, small trees)	50
	Heavy (dense brush or timber, down and dead fuel)	75

Defensible space (CSFS 6.302 Standards)

	More than 150 feet	0
	30-150 feet	50
	10-30 feet	75
	Less than 10 feet	100

Appendix B

Table B.1
Coefficient Estimates, Standard Errors, and P-values for various transformations of the Risk Averse variable in full Bivariate Ordered Probit Regression Models

Re-coding Scheme	Defensible space			Home hardening		
	Coef.	S.E.	p-value	Coef.	S.E.	p-value
Model 1: Self-assessment dependent variables (n = =1404)						
0–10 (continuous; reverse coded 0 = very willing to take risks; 10 = not at all willing to take risks)	0.019	0.012	0.120	−0.003	0.014	0.801
1 = 0–1;0 = otherwise	0.279	0.097	0.004	0.004	0.108	0.971
1 = 0–2;0 = otherwise	0.247	0.071	0.001	−0.064	0.080	0.425
1 = 0–3;0 = otherwise	0.102	0.061	0.094	−0.015	0.069	0.828
1 = 0–4:0 = otherwise	0.046	0.059	0.431	−0.006	0.066	0.925
1 = 0–5;0 = otherwise	0.011	0.063	0.858	−0.019	0.071	0.788
Model 2: Professional-assessment dependent variables (n = =1404)						
0–10 (continuous; reverse coded 0 = very willing to take risks; 10 = not at all willing to take risks)	0.028	0.013	0.031	−0.015	0.014	0.286
1 = 0–1;0 = otherwise	0.170	0.099	0.087	−0.093	0.109	0.394
1 = 0–2;0 = otherwise	0.262	0.074	0.000	−0.038	0.081	0.638
1 = 0–3;0 = otherwise	0.141	0.064	0.027	−0.060	0.070	0.389
1 = 0–4:0 = otherwise	0.126	0.061	0.041	0.008	0.067	0.909
1 = 0–5;0 = otherwise	0.053	0.066	0.421	−0.090	0.072	0.213

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