

Essays on the influence of natural disasters and extreme weather on households' resilience and
land management

by

Mariam Hamed Gharib

B.S., Egerton University, 2013
M.S., University of Delaware, 2018

AN ABSTRACT OF A DISSERTATION

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DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
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Abstract

Extreme weather events have increased in frequency and severity, and it is anticipated that these events will continue to rise into the future. These extreme weather events have affected the natural system, disrupting wildlife and ecosystem services, amongst other challenges. In order to mitigate the impacts of extreme weather events, individuals, households, and firms may need to adjust their behavior and way of life. In this study, we focus on the influence of these extreme weather events on households' resilience and land management with respect to infrastructure services, conservation and preparedness, with a more concentrated focus on wildfire events. The focus on wildfire events stems from the frequency and intensity of these events and how they have been increasing, especially in the Great Plains of the U.S. We examined how wildfire influences natural systems in the first chapter. In the other two chapters, we look at how individual behavior is shaped by exposure to severe weather events in general.

In chapter 1, we study the effect of wildfire and severe drought on Conservation Reserve Program (CRP) persistence. We define CRP persistence as the number of years in which grassland was the majority of the land use in an expired CRP contract parcel. In the literature, there is a lot of research on what influences CRP persistence, but little literature extensively examines the effects of wildfires and drought, as well as surrounding land use, on CRP persistence. To study this, we built a 10-year unique geodatabase at the CRP parcel level and used a Mixed Effects Weibull accelerated failure time model (AFTM) to do the analysis. We find that CRP persistence is 3 years on average. CRP persistence is higher if an expired CRP parcel or surrounding land is burnt by a megafire, located in mid-range drought, and increases for every increase in the percentage of grassland and open water for a 50m buffer and decreases if bordered by crops or

found in more wet areas. There is a need for policy intervention through education to encourage landowners to retain CRP-based practices and enhance wildfire mitigation land management efforts on both CRP and post-CRP lands. Alternatively, the government can increase the likelihood of reenrollment for CRP lands classified as risky areas, such as those that are less connected or surrounded by crop production and located in wetlands or areas with higher rainfall.

Chapter 2 estimates how much households are willing to pay (WTP) to avoid power outages that vary both in frequency and duration across states in the Great Plains of the U.S. because of severe weather events or natural disasters. A secondary objective was to assess the differences in WTP across different population segments, i.e. Metropolitan Statistical Areas and Non-Metropolitan Statistical Areas. With an ageing electric grid and power infrastructure that is more than 100 years old, power outages caused by severe weather events are more frequent and longer in duration, and the situation is expected to worsen in the future. Before building grid resilience and adopting different resilience technologies, we need to understand households' WTP for such technologies in the case of a severe weather outage. Using primary data from a two-stage choice experiment and a theoretically consistent framework, we find that WTP was much higher when both duration and frequency varied, but this depended on the acceptable level of duration and frequency of power outage for a household. When comparing the WTP across MSA and N-MSA, we find that it is higher for the former. The positive WTP values show that a market exists for backup services, and utility companies, government, and community members can invest in the improvement of power infrastructure reliability and resilience, depending on the cost of investment and use the WTP values for resource planning and pricing.

In my last chapter, Chapter 3, we examine the influence of alternative information sources on a household's perceived level of wildfire and disaster preparedness and perceived confidence

in being prepared for a wildfire or disaster between households in states in the Great Plains (GP) and mountainous western regions (MW) of the U.S. In the literature, understanding the effect of various disaster preparedness information channels across various geographical areas that differ in disaster preparedness resources is sparse. To do this, we analyze 3 years of an annual household disaster preparedness survey conducted by the Federal Emergency Management Agency, focusing specifically on households surveyed about wildfires. We find that the perceived level of wildfire and disaster preparedness or perceived confidence level to prepare for a wildfire or disaster does not differ between the two regions, and the effect of information sources on both is region-specific. Public announcements served as the strongest information source influencing disaster preparedness in the MW, while network sources served as the most influential information source for the GP. For the perceived confidence level to prepare for a wildfire and disaster, networks served as the strongest source, but the effect was mostly driven by MW. Practical implications suggest targeting more than one appropriate area-specific communication channel in each region for disseminating wildfire disaster preparedness information, as well as providing needed resources that ensure effective and efficient distribution of disaster preparedness information.

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Approved by:

Major Professor
Jason S. Bergtold

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Chapter 1 - Wildfire and Severe Drought Effects on Conservation Reserve Program (CRP) Persistence

1. Introduction

The Conservation Reserve Program (CRP) is the largest conservation program in the USA to enroll private lands (Barnes et al. 2023; Morefield et al. 2016; Roberts and Lubowski 2007; Bigelow et al. 2020). The program was established in 1985 by the Food Security Act to decrease soil erosion, stabilize commodity prices, improve water quality, and nurture wildlife habitat through rehabilitating highly erodible cropland with perennial conservation cover in exchange for annual rental payments (Vandever et al. 2023; Coppess 2017; USDA Farm Service Agency 2021). However, because of its limited-term contracts, the benefits from conservation under the program are not guaranteed in the long-term.

Environmental benefits from CRP participation depend on how the land enrolled in CRP is managed after contract expiration. Land that remains under CRP vegetative cover is said to persist under CRP land management conservation practices. In this study, we simply define CRP persistence as the continuance of CRP-based practices on the land after contract expiration. We measure this by the number of years the CRP-based or similar land use has been retained on a parcel of land after CRP contract expiration. In contrast, Vandever et al. (2023) were more restrictive, defining CRP land to be persistent if half or more of the land that was enrolled remains under CRP vegetative cover for 3 years or more after the expiration of the contract. Retaining land under the same vegetative land cover after a CRP contract has expired may have higher ecological benefits and potential economic benefits, as well (Barnes et al. 2023; Dayer et al. 2018; Vandever et al. 2023). Reverting land to other uses can be detrimental to wildlife habitats, soil quality, and

some of the conservation benefits achieved while the land was enrolled in CRP. If the land is used for crop production, any potential adverse effects will depend on the agricultural practices adopted and the type of crop planted (Dayer et al. 2018; Bigelow et al. 2020; J. E. Gilley et al. 1997).

CRP persistence has ranged from as low as 15% to as high as 66 % of previously enrolled land in the CRP (Sullins et al. 2021; Jessica C. Barnes et al. 2020; Roberts and Lubowski 2007). CRP persistence has been higher in drier states in the Pacific, Mountain, and Southern Plains regions of the U.S. and lower in wetter states in the Northern Plains, Lake States, and Corn Belt regions of the U.S. (Vandever et al. 2023). In the Central and Western United States, CRP persistence has varied between 19% and 84%. At least 50% of these expired CRP lands have retained CRP land cover for three or more years (Vandever et al. 2023). How long CRP practices remain on the land after the expiration of a contract depends on the type of conservation practices adopted (Jessica C. Barnes et al. 2020). Other factors that influence CRP persistence are geographical location, landscape, program experience, ease and desirability of maintaining CRP cover, aesthetic value of the land, valuation of wildlife/livestock, land quality, amongst other factors (Sullins et al. 2021; Roberts and Lubowski 2007; J.C. Barnes et al. 2023; Vandever et al. 2023).

There has been a lot of research into what happens to CRP land after contract expiration. Studies have examined land use transitions after the CRP contract expiration (Atkinson et al. 2011; Barnes et al. 2020), CRP persistence (Dayer et al. 2018; S. Jacobson 2014; Sullins et al. 2021), and factors that influence CRP re-enrollment (Roberts and Lubowski 2007; Daniel Hellerstein and Malcolm 2011; Barnes et al. 2020; Morefield et al. 2016), among other research directions. Some studies have attributed CRP land cover to causing fast-moving fires due to the nature of the

vegetation and potential fuel load that may build up on CRP lands. These fields have management restrictions that increase the fuel load and dry materials, which may increase wildfire risk (Community Wildfire Protection Plan Steering Group and Hulbert 2007; Collins 2017; Frazier 2018; Bergtold et al. 2024). High fuel loads during a period of extreme drought can further increase wildfire risk (A. L. Westerling et al. 2006). CRP land has been perceived as a fire hazard in the Mountain, Pacific, and Southern Plains regions of the U.S. by landowners (Allen and Vandever 2003; Bergtold et al. 2024). Wildfire risk on CRP land varies, becoming significantly higher during periods of greater drought severity (Hodur et al. 2002; Steiner et al. 2020, 2018).

Wallander et al. (2013) found that climatic conditions influence participation in conservation programs, including the CRP. Farmers were more willing to enroll in conservation programs in drought-prone areas (Wallander et al. 2013). Farmers viewed participation in conservation programs as a safety net when faced with high drought risk (Wallander et al. 2013). Drought conditions have influenced CRP persistence as well after contract expiration (Li et al. 2022; Aragon et al. 2025; Barnes and Dayer 2021). Aragon et al. (2025) found that in the U.S., drought was one of the factors that influenced CRP persistence after contract expiration. In Texas, Li et al. (2022) found that most CRP conversion to cropland happened during a period of extreme drought. Contrarily, J.C. Barnes and Dayer (2021) found that in the Great Plains, during a period of drought, landowners were more likely to retain CRP fields in grass or use them for grazing. However, little is known about the effect of environmental factors, especially wildfires, on landowner decisions on the reversion of expired CRP to cropland or other uses (Vandever et al. 2023).

Wildfire risk is determined by the interaction of land use and fire management decisions in an area and its surrounding areas (Butsic et al. 2015; Steiner et al. 2020). Fire proneness tends to be high in shrublands and grasslands and lower in agricultural and agroforestry areas (Carmo et al. 2011; Stavi 2019; Radeloff et al. 2023; Zhai et al. 2023). In the Great Plains, 90% of the area that is burned by a large wildfire (wildfire that burnt more than 400 ha) tends to occur in woody and grassland landscapes and is less likely in croplands, pasture/hay fields, and developed areas (V. M. Donovan et al. 2020). This is further worsened by the low rate of CRP management on expired CRP parcels, where only 39% of the parcels with persistent CRP cover are managed, but it does not specify if it is for wildfire reasons (Vandever et al. 2023). Expired CRP parcels that retain CRP-based grassland practices tend to have higher grass cover compared to active CRP contracts (Vandever et al. 2023). This may result from having no dedicated management practices that are required after contract expiration (Bigelow et al. 2020). The most common management practices used on expired CRP land are grazing, haying, and mowing (Vandever et al. 2023; Heimlich and Kula 1990). However, the intensity of activity will determine the level of vegetation cover and any potential fire risk. Excessively grazing or haying may result in a decrease in vegetation cover and an increase in bare ground, leading to a lower wildfire risk and potentially reversing the environmental benefits achieved (Steffensmeier 2025). Yet, the decision to utilize and the level of grazing, haying and mowing depends on the economic tradeoffs between maintaining prior CRP land use and management practices and the returns from grazing, haying and mowing the land and reductions in wildfire risk.

The purpose of this study is to examine how environmental factors, including wildfire risk, drought and neighboring land use, influence CRP persistence on expired CRP lands across Kansas. We define CRP persistence as the number of years in which grassland was the majority of the land

use in an expired CRP contract parcel. Between 2013 and 2016, Kansas was among the 5 states with the most expired land (532,000 acres) with less than 50% reenrolled back to CRP (Bigelow et al. 2020). We focus on the influence of two specific environmental factors, wildfires and drought. A secondary objective of the study is to better understand how neighboring land use (e.g. crop production, grassland, urban development, etc.) influences CRP persistence. Neighboring land uses may influence wildfire and drought risk management strategies, as well as land management decisions on expired CRP land. How landowners manage neighboring land may impact CRP persistence on a given parcel after CRP expiration (Barnes et al. 2023). To ensure ongoing environmental benefits of CRP land after it exits the program, policymakers and land managers need to understand whether experience with or exposure to wildfire and drought affects CRP persistence. We developed three primary research questions: (1) Does wildfire or drought affect the marginal likelihood of CRP persistence or maintaining CRP practices on the land after contract expiration?; (2) Does CRP persistence vary depending on the severity of wildfire or droughts?; and (3) Does the effect of surrounding land management influence CRP persistence? This is the first study, to our knowledge, to primarily focus on the effects of environmental factors, such as wildfire, and the percentages of neighboring land uses, such as cropland, open water and development, on CRP persistence.

Our developed geodatabase covers a period of ten years from 2012 to 2021, and we find CRP persistence is, on average, 3 years, and most CRP reversals occur within the first 2 years. Environmental factors and land use in the surrounding area played a significant role in influencing CRP persistence. Expired CRP parcels or surrounding land that were burned by a megafire had a higher CRP persistence level, while other wildfires (fires that burned less than 100,000 acres) did not influence CRP persistence. In addition, the closer a megafire is to a parcel, the greater the

likelihood of CRP persistence on the margin. Parcels that were exposed to megafires were more often surrounded by a larger percentage of grasslands. It is likely that, given the surrounding land use is primarily in grasslands, maintaining similar land covers to CRP provides higher economic returns from grazing for livestock, driving the CRP persistence.¹ Another explanation could be that landowners perceive managing the land for wildfire risk may not be effective or worthwhile, so they maintain a similar land use cover as under CRP, as it provides the highest overall return for them. We observe a positive effect of drought on CRP persistence. CRP persistence tends to be higher in drought-prone regions. This may result from a similar effect on landowner management decisions as wildfire. That is, it may be less desirable or meaningful to convert the land to an alternative land use that provides a less perceived return and may be riskier. As expected, land use in the immediate surrounding area (50m buffer) influenced CRP persistence. CRP persistence increased with each increase in the percentage of grassland and open water and decreased with each increase in the percentage of crops, with a change in the percentage of local development having no impact on CRP persistence.

This study builds on existing literature by highlighting the importance of policy interventions within the first two years of contract expiration if there is a desirability to ensure conservation benefits of CRP are retained in the longer term. Expired CRP parcels maintained in grassland practices can reach higher fuel loads that may result in faster-spreading fires. There is a need for outreach and policy efforts to enhance wildfire mitigation land management efforts on both CRP and post-CRP lands to reduce wildfire incidence. This becomes more important as CRP

¹ A limitation of our study is that we did not differentiate types of grassland management (e.g. cover, biomass levels, grazing intensity, etc.) in our study. We do though account for haying as alternative land uses. This may provide an opportunity for future research.

persistence increases with wildfire risk, especially from megafire events, which themselves may result in long-term effects on land use. Education campaigns should specifically focus on fire management to manage the high fuel loads on expired and current CRP parcels. The government can also use this information to target risky areas that are more likely to revert to other land uses, such as expired CRP parcels with higher acreage, those that are less connected to other CRP lands, those surrounded by crop production, parcels located in wetlands or areas with higher rainfall, and during periods of short-term drought. This can be done through policy changes that increase the likelihood of reenrollment in CRP.

2. Background on the Conservation Reserve Program

The CRP provides financial incentives to encourage private land conservation in the U.S. on marginal and vulnerable lands in the U.S. (Dayer et al. 2018). Payment for private land environmental services stems from experience with drought, dust storms, and economic depression during the 1930s (Claassen et al. 2008). Since 1985, the U.S. Department of Agriculture (USDA) has implemented conservation practices on agricultural working lands, marginal cropland, and for wetland restoration (Ciuzio et al. 2013).

Most CRP contracts are allocated through intermittent reverse auctions, where the landowner submits an annual rental amount they are willing to accept to establish a specific set of conservation practices (Bigelow et al. 2020). In 2019, there were 43 different Conservation Reserve Program land management practices, grouped into four broad categories: grasses, trees, wetlands, and wildlife habitat, that could be adopted on CRP lands (Bigelow et al. 2020). Other lands are enrolled through the continuous signup that targets specific CRP initiatives or a given high-priority practice, e.g. pollinator habitat and water restoration (Bigelow et al. 2020). The

benefits to the landowner for enrolling in CRP are financial incentives, enhancement and enjoyment of ecosystem services, and improvement of land quality (Bigelow et al. 2020). CRP provides an estimated annual benefit of \$1.3 billion, which accounts for 75 to 80% of the cost of CRP (Hansen 2007). Recent studies have found that the benefits of CRP exceed its cost (Johnson et al. 2016). CRP has increased average farmland value in the Mountain, Southern Plains, and Northern Plains of the U.S. by 9%, 2%, and 3%, respectively (J. Wu and Lin 2010; Allen and Vandever 2003).

CRP enrollment was highest in 2007 (36.7 million acres) and has been declining since 2012. This year, the program had the most area under contract expiration, 6.5 million acres. Enrolled acres were fewer than expired acres that year (Bigelow et al. 2020). In 2020, the area enrolled in CRP was 21.9 million acres, the lowest in 3 decades (USDA Farm Service Agency 2020). CRP has lost 10 million acres over the last 10 years, resulting in reduced environmental benefits (Vandever et al. 2023). Morefield et al. (2016) estimate that the percentage loss of CRP acreage since 2007 exceeds 25%. Most of the expired CRP lands that are lost are grasslands, followed by wildlife habitat, with the lowest being wetlands (Morefield et al. 2016). CRP lands with trees were more likely to retain 60 to 70 percent of their tree cover (Roberts and Lubowski 2007). Not all environmental benefits are lost when CRP land is converted to other land management options or uses (Bigelow et al. 2020). The extent of the potential loss of environmental effects of not re-enrolling CRP land depends on land management practices adopted and the type of crop grown if converted to cropland (Morefield et al. 2016). Growing crops on former CRP land can diminish soil and water quality, reduce wildlife habitat, and harm wildlife species, potentially undoing the benefits previously attained (Gewin et al. 1999; Gilley et al. 1997; Schlaepfer et al. 2002; Herkert 2009).

Some of the reasons that an expired CRP land is retained in grassland are for hay production, livestock grazing, aesthetic value or wildlife habitat (Janssen et al. 2008; Roberts and Lubowski 2007; Barnes et al. 2023; Vandever et al. 2023). In some cases, the conversion cost and uncertainty in future returns may warrant retaining the CRP-based practice after contract expiration (Schatzki 2003), but we don't directly consider this in our study, following (Lubowski et al. 2008). Others may retain the CRP-based practice because of their prior intention of retiring the land from crop production before enrolling the land in CRP (Lubowski et al. 2008). In a few cases, landowners may retain CRP-based practices to participate in other conservation practices in cases where land cannot be re-enrolled in CRP (Barnes et al. 2020). Landowners may also simply retain the CRP-based practice because they receive a higher utility and not for a profit motive (Kuhfuss et al. 2016). A program may positively change a landowner's perceptions of conservation and increase persistence behavior, as well (Dayer et al. 2018; Race and Curtis 2013).

3. Methods

3.1 Conceptual Framework

A landowner will choose a land use or management activity that maximizes quasi-rent minus the variable cost of that land use or management activity. We assume the quasi-rents earned by the landowner may not be purely monetary and can include nonpecuniary, option, existence and non-use values (e.g. from ecosystem services that are valued by the landowner). Quasi-rent is a temporary return above normal return that a landowner earns from investing in specific land management activities (Durlauf and Blume 2008). The quasi-rent received will depend on land characteristics such as soil fertility, climate, location and other physical characteristics that relate to the rents or returns from alternative land use options (Roberts and Lubowski 2007). In the southern Great Plains, post-CRP land use decisions are shaped by biophysical, socioeconomical,

and institutional factors (Barnes and Dayer 2021). CRP lands are privately owned, and the decision to retain CRP-based practices on the land after contract expiration will be landowner-specific and be driven by the quasi-rent received and perceived by the landowner.

Following Wu et al. (2013), we assume that a landowner's decision to retain CRP-based practices on the land in time t after the CRP contract expiration at time T_0 is a continuous process and depends on the quasi-rent received by the producer from continued CRP or conservation practices on the land, given by $U_i(t; \cdot)$. Let i represent a parcel-producer combination, i.e. expired CRP parcel d managed by producer q . Assuming that retaining the land on the same CRP-based practice generates a maintenance cost K_{it} , the net present value of the expected discounted return for the $s = t - T_0$ years for maintaining the land under CRP-based practice is: -

$$(1) \quad V_{it} = \int_{T_0}^t U_i(t) e^{-\rho t} dt - K_{it},$$

Where $U_i(t) = f(\mathbf{E}_{it}, \mathbf{P}_i, \mathbf{F}_{it}, \mathbf{C}_{it})$, $\mathbf{E}_{it}$, $\mathbf{P}_i$, and $\mathbf{F}_{it}$ are vectors of explanatory factors that influence quasi-rent or utility. $\mathbf{E}_{it}$ is a vector and denotes environmental factors. $\mathbf{P}_i$ is a vector of parcel characteristics. $\mathbf{F}_{it}$ is a vector of financial and economic market factors. Finally, $\mathbf{C}_{it}$ is a vector of factors representing the type of land cover in the surrounding land.

Changes in environmental factors ($\mathbf{E}$) influence land use changes and participation in conservation programs (Dan Hellerstein et al. 2019; Wallander et al. 2013). In this study, we examined the effects of drought and wildfire on CRP persistence. We included drought as a variable because wildfires occur most often during times of drought. We wanted to assess the effects of drought and wildfires on CRP persistence. We speculate that wildfire or drought characteristics affect CRP persistence. Previous studies have shown that the type of wildfire influences a person's response to mitigation (Wong et al. 2023). Drought also influences

participation in conservation programs (Wallander et al. 2013) and determines a landowner's decision to retain CRP practice after contract expiration (Li et al. 2022; Aragon et al. 2025; Barnes and Dayer 2021). We also included weather information, such as rainfall and temperature patterns, as they can influence decision-making for agricultural enterprises (Haigh et al. 2015; Morton et al. 2017), and CRP persistence (Sullins et al. 2021; Morefield et al. 2016).

Parcel characteristics (**P**) help capture the valuation of the land by the land owner and/or operator (Roberts and Lubowski 2007) and influence CRP persistence (Caldas et al. 2016). Land characteristics, such as soil quality, slope, or landscape characteristics, determine the suitability of land for farming after CRP contract expiration (Barnes and Dayer 2021). Size of the CRP expired parcel has also been known to influence CRP persistence (Sullins et al. 2021; Caldas et al. 2016). Another important factor is the surrounding area's land cover (**C**) for an expired CRP parcel, which has been shown to impact wildfire impacts and CRP persistence (Sullins et al. 2021). The percentage of surrounding land that was under crop production, grassland, and development, based on findings from previous studies, has been attributed to influencing CRP persistence (Sullins et al. 2021; Barnes and Dayer 2021; Berger et al. 2020).

Financial and economic market factors (**F**) play a significant role in CRP persistence (Caldas et al. 2016). For example, an increase in crop prices has been known to decrease CRP persistence (Sullins et al. 2021; Barnes et al. 2020; Daniel Hellerstein and Malcolm 2011; Stubbs 2014; Bigelow et al. 2020; Li et al. 2022). Land owners compare CRP rental rates and land rental rates when deciding to reenroll land back into CRP (Stubbs 2014), which may also influence CRP persistence.

Land can be converted to other land management options at time t after the contract expiration at time T_0 . Assume there are $n = 1, \dots, N$ alternative land use options (e.g. crop production, development, etc.) in addition to retaining the land under CRP-based practices. Let the net discounted returns for each of the alternative land use options be represented as $A_{i1}(t), \dots, A_{iN}(t)$, for $s = t - T_0$ years after contract expiration. Let ω represent the expected discounted net return for the best alternative land management option, which is given by: -

$$(2) \quad A_{i\omega} = \int_{T_0}^t A_{i\omega}(t) e^{-\rho t} dt$$

where $A_{i\omega}(t) = f(\mathbf{E}_{it}, \mathbf{P}_i, \mathbf{F}_{it}, \mathbf{C}_{it})$. We assume the same factors or considerations that would influence $U_i(t)$ influence other potential land use options.

Considering this framework, a landowner will continue to retain CRP-based practices at time t or for s years after contract expiration, if the net present value of the return (quasi-rents minus variable costs of land management) from CRP-based practices after contract expiration for s years is greater than the return from the next best alternative land management option. That is, if $\Delta \Pi_{i\omega}(\mathbf{E}_{it}, \mathbf{P}_i, \mathbf{F}_{it}, \mathbf{C}_{it}) > 0$ for the s years of maintaining CRP-based land cover after CRP expiration, where: -

$$(3) \quad \Delta \Pi_{i\omega}(\mathbf{E}_{it}, \mathbf{P}_i, \mathbf{F}_{it}, \mathbf{C}_{it}) = V_{it}(\mathbf{E}_{it}, \mathbf{P}_i, \mathbf{F}_{it}, \mathbf{C}_{it}) - A_{i\omega}(\mathbf{E}_{it}, \mathbf{P}_i, \mathbf{F}_{it}, \mathbf{C}_{it}) > 0$$

where ω is the next best alternative land management option.

A landowner will consider shifting away from CRP-based land management practices to the next best alternative land management option when $\Delta \Pi_{i\omega}(\mathbf{E}_{it}, \mathbf{P}_i, \mathbf{F}_{it}, \mathbf{C}_{it}) < 0$. The question becomes, at what point in time does a producer choose to switch to an alternative land use practice? The “optimal” time (t^*) to switch from a CRP-based practice to another land management options

is the point in time when $\Delta\pi_{it\omega}(E_{it}, P_i, F_{it}, C_{it}) < 0$ for the next best alternative land management option ω . The landowner will retain the land under the CRP-based practice otherwise. The optimal time t^* can be immediately (at time T_0) or s years after CRP contract expiration.

3.2 Empirical Model

Based on the conceptual model, we adopt an accelerated failure time model to model the duration of time of CRP persistence and the environmental, surrounding land use and other factors influencing it. The accelerated failure time model measures the survival time of an event before it fails. Survival time here refers to how long CRP-based practices remain on an expired CRP parcel before it is converted to another land management option, which is referred to as failure. That is, the duration s a parcel retains similar CRP cover after CRP contract expiration at time T_0 . Our study covers a period of ten years from 2012 to 2021, and the maximum duration s a parcel retains similar CRP cover after CRP contract expiration is 9 years, assuming the contract expired in 2012.

We observe a landowner's switching time, t^* , from a CRP-based practice to the best alternative land cover or duration, they retain the same CRP-based practice for the period of observation. To capture this, one can use a hazard function that captures the instantaneous probability at time t that a landowner will switch from a CRP-based practice to another land management option after s years or the limit of the time horizon being assessed, whichever comes first. The hazard rate based on Greene (2018) and Kiefer (1988) is written as follows: -

$$(4) \quad h_i(t) = \lim_{\Delta t \rightarrow 0} \frac{\text{Prob}(t \leq s \leq t + \Delta t | s \geq t)}{\Delta t} = \lim_{\Delta t \rightarrow 0} \frac{F(t + \Delta t) - F(t)}{\Delta t} = \frac{f(t)}{S(t)}$$

where $h_i(t) = \frac{-d \ln S(t)}{dt}$, $f(t) = S(t)h_i(t)$, and s is a random variable that represents switching time $(t - T_0)$, which has a probability density distribution of $f(s)$ and a cumulative distribution

function $F(s)$. $S(t)$ is a survival function that represents the probability that the landowner will retain similar CRP-based practice and not switch to other land management options at time t . The timing decision is based on the conceptual framework, and is a function of a number of factors, E_{it} , P_i , F_{it} , and C_{it} . E_{it} (Environmental factors) capture parcel experience with wildfire and drought by examining wildfire-damage severity, drought intensity, and parcel distance to the closest wildfire. We also capture wildfire-damage severity on the nearest surrounding land. We distinguished wildfire-damage severity and parcel distance to the closest wildfire by whether it was a megafire or other wildfire for both the parcel and the surrounding land. A megafire is a wildfire that burns more than 100,000 acres, with other wildfires representing those burning less than 100,000 acres. E_{it} also contains climatic conditions such as precipitation and temperature patterns. We included the size of the CRP expired parcel, soil type, land capability classification, and erosion capability, such as wind and water erodibility measures, to represent parcel characteristics (P_i). For surrounding land use (C_{it}), we examine the percentage of surrounding land that was under crop production, grassland, development, and open water. Finally, we consider the ratio of CRP rental rates to land rental rates (land valuation) and crop price index as direct economic factors, as well as and population density as a proxy to capture additional development pressures (F_{it}).

CRP-expired land often extends CRP based practice after the expiration of the contract (Roberts and Lubowski 2007) and most reversal of CRP practices to other land use occurs within five years of contract expiration (Bigelow et al. 2020; Sullins et al. 2021; Vandever et al. 2023; Aragon et al. 2025). Some studies attribute that CRP persistence decreases with how long the contract has expired (Barnes et al. 2020). Based on this, we included the year of contract expiration (Y_{ji}) making the timing decision as a function of E , P , F , C , and Y .

We model the hazard function following Canales et al. (2020) and Sullins et al. (2021). We assume the hazard function has a baseline hazard $h_0(t_{ji})$ that is common to all landowners in the same county. Grouping observations at the county level allows for capturing of differences in cultural practices that are not directly observed (Becker et al. 2022). Also, CRP persistence depends on the geographical location (Vandever et al. 2023; Sullins et al. 2021). We also incorporate the effects of exogenous variables ($\mathbf{E}, \mathbf{P}, \mathbf{F}, \mathbf{C}$, and Y) on the hazard rate since they influence the timing decision. Thus, the hazard rate function is specified as:

$$(5) \quad h(t_i, \mathbf{E}_{it}, \mathbf{P}_i, \mathbf{F}_{it}, \mathbf{C}_{it}, Y_i) = h_0(t_i) \exp(\beta_1 \mathbf{E}_{it} + \beta_2 \mathbf{P}_i + \beta_3 \mathbf{F}_{it} + \beta_4 \mathbf{C}_{it} + \beta_5 Y_i)$$

where $h_0(t_i)$ represents the baseline hazard at time t , $\mathbf{E}_{it}$, $\mathbf{P}_i$, $\mathbf{F}_{it}$, and $\mathbf{C}_{it}$, are all vectors of explanatory variables, and Y_i is an explanatory variable. $\beta_1, \beta_2, \beta_3, \beta_4$ and β_5 are parameters to be estimated. $\mathbf{E}_{it}$ is a vector of environmental factors, $\mathbf{P}_i$ is a vector of parcel characteristics, $\mathbf{F}_{it}$ is a vector of financial and economic market factors, $\mathbf{C}_{it}$ is a vector of factors capturing the type of land cover surrounding the parcel, and Y_i represents the year the contract expired. We dropped the index $j = 1, \dots, k$ that represents the various counties in a state in the equation to simplify the notation. We assume an exponential specification to ensure the hazard function remains positive (Canales et al. 2020; Greene 2018).

We assume that the distribution of s follows a Weibull distribution (Greene 2018; Canales et al. 2020), giving the following specification for the baseline hazard function, which is a hazard that is common to all the landowners in the county.

$$(6) \quad h_0(t_i) = P t^{P-1} \exp(G_i).$$

P is a scale parameter. When $P > 1$, then the probability of maintaining CRP-based practice to other land management options increase monotonically with time, and the reverse if $P < 1$. Given

changes in agricultural policies and land management across the agricultural landscape of Kansas (e.g., county- and state-specific conservation options, landowner management style, and specific practices), we assume that there is unobserved heterogeneity across counties. To capture this, we assume that G_i is a random intercept in the baseline county hazard function at the county level.² That is $G_i = \gamma + \sigma_G \vartheta_i$, where $\vartheta_i \sim N(0,1)$. Putting all this together, the hazard rate is given by:

$$(7) \quad h_i(t_i, x_{it}) = P t^{P-1} \exp(G_i + \beta_1 E_{it} + \beta_2 P_i + \beta_3 F_{it} + \beta_4 C_{it} + \beta_5 Y_i).$$

To compute how long before a landowner switches the CRP-based practice to another land management option (CRP persistence), we estimate the logarithm of the hazard rate function shown above. The log of CRP persistence is estimated using the following regression function:

$$(8) \quad \ln s_i = G + \beta_1 E_{it} + \beta_2 P_i + \beta_3 F_{it} + \beta_4 C_{it} + \beta_5 Y_i + \sigma \varepsilon_i$$

where $\sigma = \frac{1}{P}$ is a scale parameter and ε is a mean zero stochastic error term with Type-1 extreme value distribution.

We estimated the duration of persistence as a Mixed Effects Weibull accelerated failure time model (AFTM). That is, we include a random intercept that varies across counties to capture unobserved geographical heterogeneity as specified earlier. We also estimated a fixed-effects model at the county level as a robustness check. Duration of persistence measures how long the expired CRP-based practice was maintained on the land after contract expiration; we refer to this time as s years in the conceptual model, which is $t - T_0$. The detailed mixed-effect Weibull AFTM we specified is given in equation (9).

² Ideally, we would make G_{ji} a random intercept across producers, but due to numerical issues, estimation of such a model would not reliably converge to a solution using multiple algorithms and starting points. We instead assume that unobserved heterogeneity arises at the county level, which did allow for an estimable model.

$$\begin{aligned}
(9) \quad \ln s_i = & G_i + \mu_1 \text{Clay}_{it} + \mu_2 \text{Silt}_{it} + \mu_3 \text{Kw factor}_{it} + \mu_4 \text{WEI}_{it} + \mu_5 \text{Acres}_{it} \\
& + \mu_6 \text{Acres}^2_{it} + \mu_7 \text{Land Class}_{it} + \mu_8 \text{Land Class}_{it} * \text{Acres}_{it} \\
& + \mu_9 \text{Laspeyres crop index}_{it} + \mu_{10} \text{Time 0}_{it} + \mu_{11} \text{Mavetemp_10yrlag}_{it} \\
& + \mu_{12} \text{Maveprep_10yrlag}_{it} + \mu_{13} \text{Mavepdsi_10yrlag}_{it} \\
& + \mu_{14} \text{Nearest wildfire}_{it} + \mu_{15} \text{Megafire}_{it} + \mu_{16} \text{Megafire}_{it} \\
& * \text{Nearest megafire}_{it} + \mu_{17} \text{Percent parcel burnt}_{it} \\
& + \mu_{18} \text{Megafire damage}_{it} + \mu_{19} \text{Percent parcel burnt}_{it} \\
& * \text{Megafire damage}_{it} + \mu_{20} \text{Percent buffer burnt}_{it} \\
& + \mu_{21} \text{Megafire buffer damage}_{it} + \mu_{22} \text{Percent buffer burnt}_{it} \\
& * \text{Megafire buffer damage}_{it} + \mu_{23} \text{Perbuffer50m_Crop}_{it} \\
& + \mu_{24} \text{Perbuffer50mDeveloped}_{it} + \mu_{25} \text{Perbuffer50m_water}_{it} \\
& + \mu_{26} \text{Perbuffer50m_grass}_{it} + \mu_{27} \text{Land valuation}_{it} + \mu_{28} \text{Pop estimate}_{it}
\end{aligned}$$

Table 1.2 describes the explanatory variables included in the model. We include four interaction terms: land capability class and acres, nearest wildfire distance and megafire burn, megafire damage and percentage of the parcel burnt, and megafire damage and percentage of the buffer burnt to capture heterogeneity and areas of interest that were used to refine the study.

We estimate the mixed-effects Weibull AFTM using simulated maximum likelihood estimation methods (StataCorp 2025). We use the mestreg command in Stata to estimate the model. Mestreg command fits a mixed-effects parametric survival models using adaptive Gaussian quadrature; in our case, we use seven integration points. We clustered standard errors at the county level because landowners in the same county share similar characteristics, and hence the standard errors are likely to be correlated. Parameters from the Mixed Effects Weibull AFTM can be used to assess the influence of factors on the direction of the switch time to or from CRP-based practices on a parcel of land. A positive (negative) coefficient of the Mixed Effects Weibull AFTM shows that CRP persistence increases (decreases) over time, and we plot Kaplan-Meier curves in STATA to estimate CRP persistence percentages over time. For magnitude changes, we estimated the average marginal effect (AME) of a unit change in an explanatory variable, i.e. **E**, **P**, **F**, and **C**

(Canales et al. 2020). Based on Canales et al. (2020), the percentage change in AME for an explanatory variable such as E_k (environmental factors) is given by:

$$(10) \% \Delta AME = \frac{s_i(E_{k+1}) - s_i(E_k)}{s_i(E_k)} = [\exp(\beta_1) - 1] \times 100,$$

where $s_i = \exp(G + \beta_1 E_{it} + \beta_2 P_i + \beta_3 F_{it} + \beta_4 C_{it} + \beta_5 Y_i) \exp(\sigma \varepsilon)$.

4. Data

Various geospatial datasets to assess the effects of wildfire and drought on CRP persistence were used to construct a unique geodatabase for this study. CRP persistence is the number of years in which grassland was the majority of the land use in an expired CRP contract parcel. The scale of the analysis is at the CRP parcel level. We obtained CRP parcel boundaries, management practices and contract information for this study directly from USDA, Farm Service Agency through a Memorandum of Understanding. The analysis conducted is for Kansas, which has 26,284 parcel-level observations that were over an acre, managed mostly as grasslands, and at some point, had an expired CRP contract that was not immediately reenrolled in CRP, and had at least 1 year of observation after the CRP contract expired. The geodatabase developed covers a period of 10 years, 2012-2021, and we use ArcGIS to do all processing for GIS data layers or geospatial data.

We only use CRP parcels that were over an acre, managed mostly as grasslands, and at some point, had an expired CRP contract that was not immediately reenrolled back to CRP, and had at least 1 year of observation after the CRP contract expired³. We focused on CRP grassland

³We initially had 72,426 parcel-level observations, of which 13,104 (18.09%) observations were still active contracts, 19,153 observations were parcels that were immediately reenrolled (26.44%) back to CRP (Scenario 1), and 40,169 (55.46%) had an expired CRP contract at some point. Of the 40,169 expired CRP contract, we dropped 13 observations that had missing CRP based practice at contract expiration, 10 observation with missing information on CDL land

because prairie grasses have been known to increase fuel load, increasing wildfire risk and intensity (Collins 2017; Frazier 2018). To determine the CRP persistence level, we first had to determine whether the CRP contract had expired and in which year it expired. If the expired contract was immediately renewed, we dropped those observations and retained those that were renewed at least one year later after contract expiration.⁴ We then obtained information on the CRP-based practice from the expired contract. We retained expired CRP parcels that were not buffers, and the majority of the land use was under grassland.⁵

We created observations for each year from the expiration date to 2021 for expired CRP parcels. In each year of observation, we obtained land use from crop data layers (CDL) in ArcGIS, sourced from the USDA National Agricultural Statistics Service (2024). The CDL provides annual land-use information, including categories of cultivated crops, grassland, shrubland, development, and open water. We resample the CDL layer from a 30m spatial resolution to a 10 meters spatial resolution to increase spatial accuracy. However, we cannot tell the difference between a CRP

use, 3536 observations that were not managed as grasslands based on the CRP contract, 2593 observation that had the majority of the land use that was not grassland at contract expiration based on CDL classification, and 7,729 observations that had CRP contract expired in 2021 (the last year of our study period). After this adjustment, we were left with 26,288 parcel-level observations and dropped an additional 4 observations with missing values for one of the explanatory variables.

⁴If we had multiple expired contracts but the difference between the contracts was 5 years or less, we treated the first contract as an extension and the second as an expired contract. We repeated the same process for cases with more than 2 expired contracts between 2012 and 2021. After correcting for this, none of the observations had more than 1 expired contract between 2012 and 2021.

⁵ We retained the following CRP practice number; CP1 (establishment of permanent introduced grasses & legumes, CP10 (Grass already established), CP12 (Wildlife food plot), CP18 (Establishment of permanent vegetation to reduce salinity), CP2 (Establishment of permanent native grasses), CP25 (Rare and declining habitat), CP38E (State acres for wildlife enhancement (SAFE), CP4 (Permanent wildlife habitat), CP42 (Pollinator habitat), 87 (Establishment of permanent introduced grasses and legumes), and 88(CRP grassland) CRP practices.

grassland practice and a regular grassland or pasture. We overlaid the CDL yearly layer to the CRP boundaries layer, and allocated land use to the land use that was the majority for each year of observation. However, a few observations were inconsistent; that is, the majority of the land use was not grassland in the year the contract expired, so we dropped these limited observations. We then calculated CRP persistence in years by counting the number of years the CRP-based practices had been retained on the land after contract expiration. If it switched to another land use, we recorded the event year and dropped every observation where the year was greater than the event year. We recognize that this is a limitation of the current study in that we are unable to differentiate between grassland management options, including CRP practices, pasture, grazing, etc. Future research could focus on this using remote sensing techniques, but that was beyond the scope of this study (Wang et al. 2022).

Based on the data, we observe seven CRP persistence scenarios for a parcel that could arise after CRP contract expiration. Table 1.1 provides a detailed description of each scenario. In Scenarios 1, 2, 3, and 4, the expired CRP parcel is reenrolled in CRP, but the timing of enrollment differs across scenarios and determines whether the CRP-based practice is maintained. The other three remaining scenarios, 5, 6, and 7, pertain to an expired CRP contract that was never re-enrolled during the period of observation. The three scenarios differ in whether CRP-based practice was changed to another land management option and when that change occurred. It is important to note that in cases where a landowner switched between CRP and another land management option a couple of times, we considered only the period between the expiration year and the first switch when assessing persistence. We therefore ignore whether a parcel was eventually reverted to a CRP-based practice after being converted to a non-CRP-based practice. We dropped Scenario 1 because it consists of CRP contracts that were immediately re-enrolled in CRP; all other scenarios

are included in the sample. For Scenario 2, Scenario 3, and Scenario 4, the contracts were renewed at least one year after contract expiration. If the CRP-based practice was retained between contracts, we captured CRP as the total number of years between the expiration year and 2021. However, if CRP-based practice changed between contracts, then CRP persistence was the difference between the event year when the landowner changed the land use and the expiration date. For the acreage of expired CRP parcels, we used the CRP boundaries layer and computed the acreage using the calculate geometry attributes tool in ArcGIS.

Table 1.1. CRP Persistence Scenarios for a Land Parcel Previously in the CRP

CRP Persistence Scenario	CRP Contract Renewed	Time of CRP Contract Renewal	Change in CRP-based practice	Time of CRP-based practice reversal	Short Description
Scenario 1	YES	Immediately	NO	-	Full CRP persistence and always active CRP contract
Scenario 2	YES	Future date	NO	-	Full CRP persistence and renewed contract
Scenario 3	YES	Future date	YES	Immediately	Zero CRP persistence and renewed contract
Scenario 4	YES	Future date	YES	Future date	Partial CRP persistence and renewed contract
Scenario 5	NO	-	NO	-	Full CRP persistence and expired contract
Scenario 6	NO	-	YES	Immediately	Zero CRP persistence and expired contract
Scenario 7	NO	-	YES	Future date	Partial CRP persistence and expired contract

Data on wildfire occurrence, severity, boundaries, and ignition points were obtained from various sources in the Southern Great Plains: Monitoring Trends in Burn Severity (MTBS): <https://www.mtbs.gov/>, National Interagency fire center and historic Geospatial Multi-Agency

Coordination Group (GeoMAC) perimeters: <https://data->

nfc.opendata.arcgis.com/datasets/48978dc5987e4fc19dce61ebdf02683b/about and Kansas Forest Service: <https://hub.kansasgis.org/>. We used ArcGIS software to calculate wildfire-damage severity and parcel distance to the closest wildfire for each year from 2012 to 2021. We overlaid each year's wildfire boundary layer, i.e., 2012-2021, on the CRP boundaries layer and obtained information on the nearest wildfire distance in km and the percentage of the area burned by a wildfire.

We were interested in the influence of megafires; we used the wildfire boundary layer to create a megafire boundary layer. A megafire is a fire that burns 100,000 acres of land or more. We computed the area burnt for each wildfire in the wildfire boundary layer and dropped any wildfire that burned less than 100,000 acres for each year from 2012-2021. We then overlaid the megafire boundary layer for each year on the CRP boundaries layer to obtain information on the nearest megafire distance in km and the percentage of parcel area burnt by megafire from 2012-2021.

We were to explore the influence of wildfire-damage severity on the surrounding land on CRP persistence. We created a 1000m buffer for each expired CRP parcel in ArcGIS using the CRP boundaries layer. A 1000m buffer captures the burnt area in the surrounding landscape in close proximity. This was done by using a buffer tool that adds a 1000m buffer around the expired CRP parcel in the CRP boundaries layer. We then used an erase tool to remove the area of the expired CRP parcel, leaving only the 1000m buffer. Using the created 1000m buffer layer, we intersected it with each wildfire and megafire boundary layer between 2012 and 2021 to obtain the percentage of the 1000m buffer burned by wildfire and megafire and the nearest distance to a wildfire and megafire for each year in the study.

For parcel characteristics, we obtained information on soil type, land capability classification, and erosion capability from the California Soil Resource Lab (2025) that aggregates data from the Soil Survey Geographic Database (SSURGO) (UC Davis Soil Resource Laboratory 2025). In the study, we used the land capability class for non-irrigated land and the percentage by weight for sand, clay, and silt. We used the land capability class for non-irrigated land because we focused only on CRP land under grassland. We also included the Kw factor and wind erodibility index (WEI), which measures soil erosion susceptibility to water and wind, respectively. We used soil properties measured at 0-25 cm depth. Soil properties were not measured yearly and are assumed constant over time.

To capture the influence of land use for surrounding land, we estimate the percentages of surrounding land under crop production, grassland, development, and open water around a CRP parcel in ArcGIS. We do this using two buffers, a 50m buffer and a 1000m buffer. A 50m buffer captures the influence of immediate land use around the buffer, while a 1000m buffer captures land use for the surrounding landscape up to 1 km distance. We use the tabulate Area tool in ArcGIS to compute the area for different land uses. The two-input raster used was the 50m buffer and the CDL yearly layer. To obtain the percentage for each land use, we divided the area of the specific land use by the total area of the expired CRP parcel. We retained the percentages of crops, developed land, open water, and grass within a 50m buffer and a 1000m buffer for each parcel for each study year.

We supplement these geospatial datasets with a calculated Laspeyres price index using state crop price levels and harvest data at the county level for four major crops in Kansas: corn, sorghum, wheat, and soybeans. The state crop price levels and state harvest data were obtained

from the U.S. Department of Agriculture, National Agricultural Statistics Service (USDA-NASS) (2025) and county harvest data were sourced from the Farm Service Agency (FSA) (2025). The Laspeyres index is a widely used measure of price changes over time, holding quantity constant at the selected base year. The index is easier to compute and interpret (Abe 2025; Goldschmidt et al. 1973; Christensen 1975; Wahtra and Johnsson 2025). We decided to use 2010 total production as the fixed base weight for index calculation. The formula is shown below; we have suppressed the county index $j = 1, \dots, k$ to simplify the notation.

$$(11) \text{Laspeyres Price Index}_t = \frac{\sum_{i=1}^k (P_{it} * Q_{it_0})}{\sum_{i=1}^k (P_{it_0} * Q_{it_0})} * 100,$$

Where $k = 1, 2, 3$, and 4 , representing the crop codes for the four crops: corn (1), sorghum (2), wheat (3), and soybeans (4), with the numbers in brackets representing the crop code. Q_{it} is the base year 2010, P_{it} represents the price for each crop at time t , P_{it_0} is the price for each crop in 2010 (base period), Q_{it} is the quantity for each crop at time t , and Q_{it_0} is the quantity for each crop in 2010.

To estimate the Laspeyres price index, we first adjusted the state crop prices using the producer price index (PPI) sourced from U.S. Bureau of Labor Statistics (2025) with 2021 as our base year, to obtain P_i at various years (2010-2021). We then computed total production (Q_{it}) per county by multiplying the harvested acreage by the yield per acre. For any missing county yield-per-acre data, we used a regional average. We multiplied the 2010 total production per county by adjusted state crop prices for each year from 2010-2021 for corn ($P_{1t} * Q_{1t_0}$), sorghum ($P_{2t} * Q_{2t_0}$), wheat ($P_{3t} * Q_{3t_0}$), and soybeans ($P_{4t} * Q_{4t_0}$) to get the value of production for each crop for each year. We then estimate the yearly Laspeyres price index by summing the value of

production for corn, sorghum, wheat, and soybeans for each county ($\sum_{i=1}^k (P_{it} * Q_{it_0})$), and divided by the value of total production for the four crops in 2010 ($\sum_{i=1}^k (P_{it_0} * Q_{it_0})$).

We followed the same process and computed the state Laspeyres price index by using the state mean crop prices, mean yield per acre, and harvested acreage for each of the four crops. For counties with missing production values for any of the four crops, we used the state Laspeyres price index. We computed a lagged crop price index, a two-lagged crop price index, and a two-year lagged moving-average crop price index. The two-year lagged moving average was used as our base variable, with the other crop price indices used as robustness checks.

Yearly CRP rental rates and land rental rates were obtained from Farm Service Agency (FSA) (2025a) and U.S. Department of Agriculture, National Agricultural Statistics Service (USDA-NASS) (2025). In some years, land rates were missing for some counties, so we used an average land rate from neighboring counties. We had missing values in 2015 and 2018, as well. For the missing land rates for 2015, we used the average of 2014 and 2016, and for 2018, we used the average of 2017 and 2019. We obtained land valuation by dividing the CRP rate by the land rental rate for each county in each year of the study. Population estimates per 1000 people were obtained from Census Bureau's Population Estimates Program (PEP) (2025) and also covered a 10-year period. We had no missing county information for any of the years.

Temperature and precipitation data were obtained from PRISM (2025), and the drought indices were obtained from Abatzoglou et al. (2025). We used the Palmer Drought Severity Index (PDSI) because it is a widely used and reliable measure of long term drought and drought risk. The index is suitable for areas with similar topography and accounts for geographical differences (Becker et al. 2022; Wallander et al. 2013; Hayes et al. 2002). We also did a robustness check by

using the Standardized Precipitation Index (SPI) that measures long-term drought risk and the Palmer Z-index (Z-index) that measures short-term drought risk. We downloaded monthly values from 1989 to 2021 for temperature, precipitation, PDSI, SPI, and the Z-index. We use extract multi values to points tool in ArcGIS to extract parcel-specific temperature, precipitation, PDSI, SPI, and Z-index from the various geospatial layers. We first computed a yearly value, and then a one-year lagged value, a 2-year lagged moving average, a 5-year lagged moving average, and a 10-year lagged moving average for the measures of temperature, precipitation, and drought indices in STATA. Our base category was a 10-year lagged moving average for weather variables and drought, as it captures weather trends. We conducted robustness checks using the other measures to assess the impact of different time horizons.

Table 1.2 shows the mean and standard deviation of the set of dependent and explanatory variables used in the empirical model. The dependent variable is CRP persistence (survival time) and captures how long the parcel retains the CRP-based practice after CRP contract expiration. The mean CRP persistence for a CRP-based practice was 3.32 years, and persistence ranged between zero and nine years. In Figure 1.1, we show the mean persistence level for each county in Kansas across expiring CRP parcels.

Table 1.2. Descriptive Statistics and Definitions for Dependent and Explanatory Variables

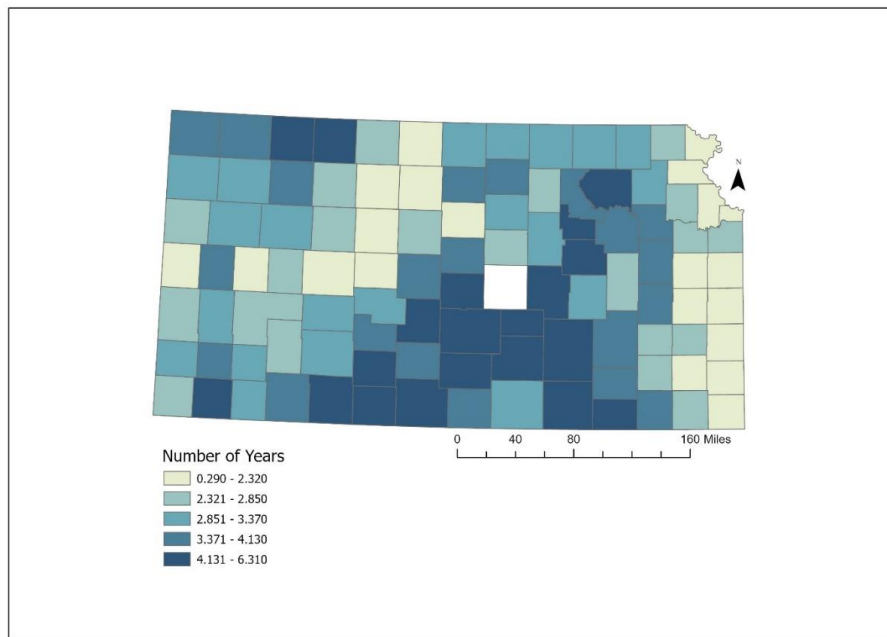
Variable	Description	N ^a	Mean (Standard Deviation) ^b
Dependent variable			
CRP Persistence	Number of years CRP-based practice has been retained on the land after contract expiration	26284	3.32 (2.98)
Cross-Sectional Explanatory Variables			
Clay	Per cent of clay by weight	26284	23.86 (7.87)
Silt	Per cent of silt by weight	26284	49.60 (16.40)
Kw factor	Measures the susceptibility of soil to detachment caused by runoff or raindrop impact	26284	0.35 (0.06)
WEI	Wind erodibility index (WEI) measures the susceptibility of soil to wind erosion	26284	68.00 (26.42)
Acres	Size of expired CRP parcel (acres)	26284	37.36 (53.12)
Land class	Land capability class	Class 1 (Base and most suitable for crop production)	130 130.00 (0.49%)
		Class 2	10232 38.93
		Class 3	10972 41.74
		Class 4	2629 10.00
		Class 5	62 0.24
		Class 6	2140 8.14
		Class 7 (Least suitable for crop production)	119 0.45
Time 0	CRP Contract Expiration Year (T0)	T0=2012	4443 16.90
		T0=2013	2644 10.06
		T0=2014	2762 10.51
		T0=2015	1910 7.27
		T0=2016	2625 9.99
		T0=2017	2171 8.26
		T0=2018	2375 9.04
		T0=2019	879 3.34
		T0=2020 (Base)	6475 24.63
Time-varying explanatory variables			
Mavetemp_10yrlag	10-year lagged moving average temperature (Celsius)	96042	12.86 (0.86)
Maveprep_10yrlag	10-year lagged moving average precipitation (millimeters)	96042	60.39 (15.71)
Mavepdsi_10yrlag	10-year lagged moving average PDSI score	96042	1.44 (0.72)
Nearest wildfire	Distance to the nearest wildfire (Kilometers)	96042	62.53 (48.20)
Nearest megafire	Distance to the nearest megafire	96042	337.14 (269.45)
Megafire	=1 if we had a megafire in that year	96042	70.85
Percent parcel burnt	Per cent of the expired CRP parcel that was burned by	96042	0.26

Variable	Description	N ^a	Mean (Standard Deviation) ^b
	wildfire		(4.98)
Percent buffer burnt	Per cent of the 1000m buffer that was burned by wildfire	96042	0.24 (4.17)
Megafire damage	=1 if a megafire caused wildfire damage on the parcel	96042	0.16
Megafire buffer damage	=1 if a megafire caused wildfire damage on the 1000m buffer	96042	0.20
Perbuffer50m_crop	Percentage of crops on a 50m buffer of the surrounding land	96042	25.66 (25.87)
Perbuffer50m_develo ped	Percentage of developed land on 50m buffer of the surrounding land	96042	12.04 (13.19)
Perbuffer50m_water	Percentage of open water on 50m buffer of the surrounding land	96005	0.32 (2.02)
Perbuffer50m_grass	Percentage of grass on a 50m buffer of the surrounding land	96005	48.19 (28.28)
Perbuffer1000m_cro p	Percentage of crops on a 1000m buffer of the surrounding land	96042	43.14 (24.58)
Perbuffer1000m_dev eloped	Percentage of developed land on a 1000m buffer of surrounding land	96042	4.50 (3.13)
Perbuffer1000m water	Percentage of open water on 1000m buffer of the surrounding land	96042	0.48 (1.27)
Perbuffer1000m_gras s	Percentage of grass on a 1000m buffer of the surrounding land	96042	39.51 (24.85)
Land valuation	Ratio of CRP rental rates to land rental rates for pasture	96042	17.94 (6.77)
Pop estimate	Population estimates per 1000 people	96042	17.15 (35.10)
Laspeyres crop index	The mean two-year lagged moving average crop price index	96042	87.48 (39.91)

^a N is different for Perbuffer50m_water and Perbuffer50m_water because the land use was missing.

^b For categorical variables, like land capability class and expiration year, the mean represents the frequency of occurrence of a given variable.

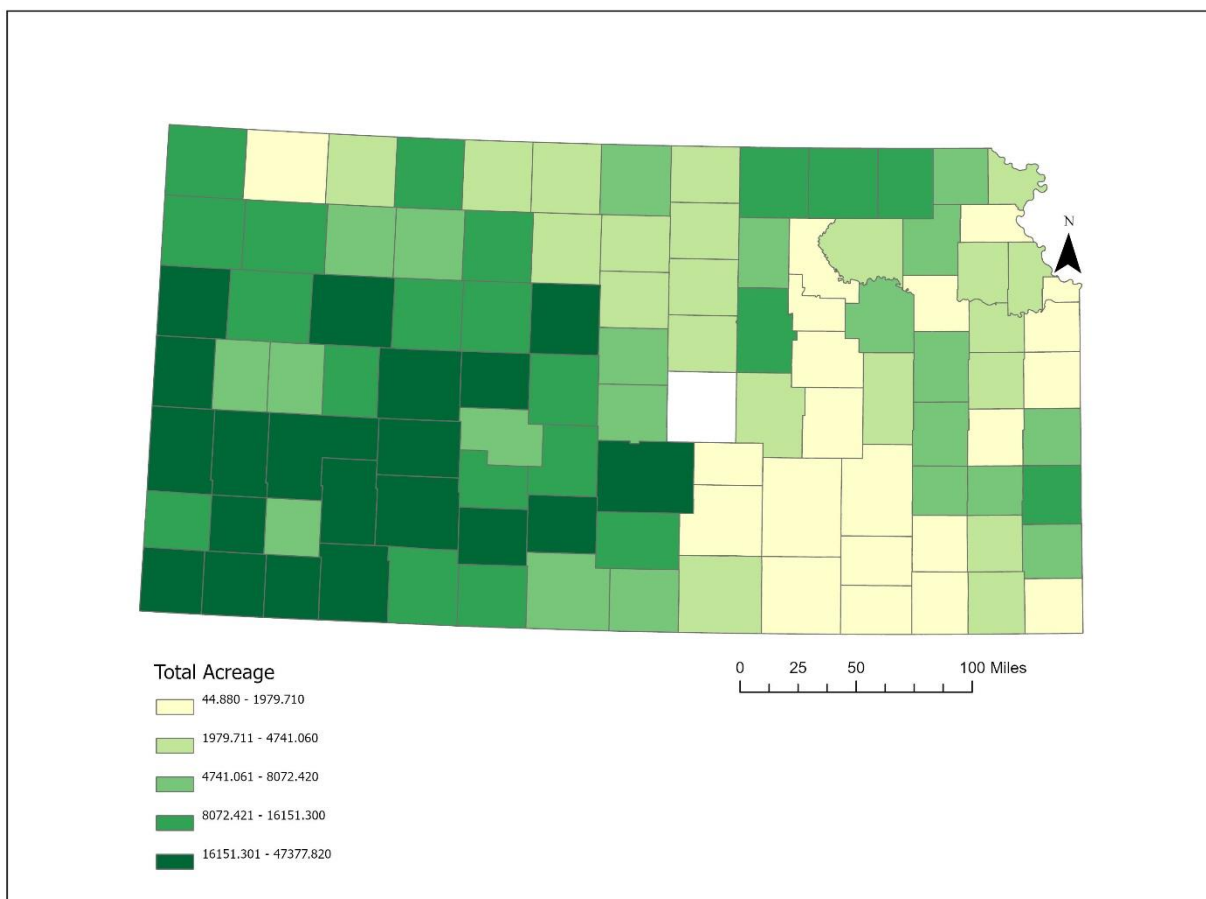
Figure 1.1. Map of CRP Persistence per County of Expiring CRP Parcels between 2012-2021



We classified the explanatory variables into four groups: parcel characteristics, type of land cover for surrounding land, environmental factors, and financial and economic markets. For parcel characteristics, we included size of the parcel in acres, percentage weight of silt and clay, land capability class for non-irrigated land, kw factor, and wind erodibility index (WEI). On average, expired CRP contract parcels were about 37.36 acres in size. Figure 1.2. shows the total acreage of CRP land that was under CRP contracts between 2012 and 2021. The soil composition of these expired CRP contract parcels was, on average, 50% silt, 24% clay, with the rest constituting sand. The majority of expired CRP contract parcels were classified in class 3 and class 2 of the land capability class at 42% and 39%, respectively. Two other classes, class 4 and class 6, had about 10% of the observations each, with the remaining classes accounting for less than 1% each. The suitability of land for crop use decreases with an increase in class value (USDA 2014). Classes 1 to 4 are suitable for crop production if properly managed, pasture production, and woodland.

Classes 5 to 7 are not suitable for crop production without specialized management but are good for permanent covers such as grasses and trees, and class 8 is suitable for recreation and wildlife habitat (USDA 2014). The mean WEI was 68.00, and the higher the erodibility index, the higher the wind erosion. As for the Kw factor, the mean was 0.35, with higher values indicating that the soil is more susceptible to detachment caused by runoff or raindrop impact (USDA 2024).

Figure 1.2. Total CRP Acreage per County from 2012 to 2021.



In order to capture trends in environmental factors, we used a 10-year moving average as a base. The mean 10-year moving average precipitation was 60.39 millimeters and 12.86° Celsius for temperature. The mean 10-year moving average PDSI was 1.44, depicting a slightly wet period.

There were some parcels that had experienced extremely wet conditions and others that had incipient dry spells. The classification of PDSI was based on Hayes et al. (2002). As for wildfires, we were interested in the distance to the closest wildfire and megafire, if a parcel and surrounding area were burnt during a megafire event, and the percentage of the parcel and surrounding land that was burnt by any wildfires. The mean distance to the closest wildfire was 62.53km and 337.14 km for a megafire. On average, only 0.26% of expired CRP contract parcels were burnt by any wildfire, and megafires burned 0.16% of these parcels. In order to determine the effect of wildfire on surrounding land, we created a 1000m buffer around the expired CRP contract parcel, and on average, a slightly higher percentage of buffers were burnt, i.e., 0.24% of the 1000m buffer and 0.20% of these parcels were burnt by megafires.

We also created a 50m buffer to capture the land management activities for the surrounding land of the expired CRP contract parcel. We did not capture all land management options, as we were only interested in the percentage of the area under grassland, open water, crops, and development. The mean percentage for the area of land around a parcel was 48.19% devoted to grassland, 0.32% to open water, 25.66% to crop production, and 12.04% to development. Land use was much different for a 1000m buffer; it was 39.51% for grassland, 43.14% for crop production, 4.50% for development, and 0.48% for open water. It was felt that the 50m buffer was a much better indicator of the influence of surrounding land, as it captures the immediate land use around the CRP parcel and not up to 1 km away.

We captured financial and economic market factors using land valuation, population estimates, and crop price indices. The mean population per county was 17,155 people, and the rental payments received from CRP per county were always higher than those of renting land for

pasture. The mean land valuation measure, which was $\left(\frac{\text{CRP rental rates}}{\text{Land rental rates}}\right)$, was 17.94. The population was measured in thousands of people. The mean two-year lagged moving average crop price index was 87.48, indicating a decrease in the prices of goods based on the 2010 base year. However, there were some cases where the price index more than doubled and instances where the price index was about half the base year index, indicating fluctuations in crop prices over the period for the study.

5. Results

5.1 Summary Statistics of CRP Persistence

CRP persistence in this study captures how long land has persisted in a CRP-based practice after contract expiration. We observed six CRP persistence scenarios as detailed in Table 1.1. The largest category, representing 54% of the parcels examined, was Scenario 5 and constituted land that retained the same CRP-based practice after contract expiration. It was followed by scenario 7 with partial CRP persistence on an expired contract at 17%. Partial CRP persistence means that CRP-based practice was not retained for the entire observation period after contract expiration but persisted for at least one year. This was followed by scenario 6 at 15%, where land was immediately converted after contract expiration, indicating zero CRP persistence. The remaining 14% of the observations were parcels that were re-enrolled in CRP after contract expiration. Of these, 13% maintained the same CRP-based practice between contracts (Scenario 2). For the two remaining scenarios, Scenario 3 and Scenario 4, which both consisted of less than 1% of total parcels being examined, the former represented parcels where there was a change from the CRP-based practice immediately (zero CRP persistence), and for the latter, CRP-based practice persisted for at least one year after contract expiration (partial CRP persistence).

Although the average CRP persistence was 3.32 years, it varied across the different CRP persistence scenarios. In Table 1.3, we show persistence in years for each CRP category and the percentage of observations in each category. The mean CRP persistence was highest in Scenario 2 at 5.65 years, with grassland practices persisting between CRP contract expiration and renewal. This scenario was followed by Scenario 5 at 4.07 years, which had full CRP persistence but never renewed the CRP contract. The third longest was Scenario 7 at 2.27 years with partial CRP persistence, with the parcel never being re-enrolled into a contract. The least persistent was Scenario 4 at 1.84 years, which had partial CRP persistence, meaning CRP grassland practices persisted for a period of time, but land was eventually converted to another use (crop production, development, etc.) prior to the parcel being re-enrolled into the CRP. In Scenarios 3 and 6, the CRP persistence was zero as it constituted parcels that immediately reverted to other land management options for land that was re-enrolled back to CRP and those that never renewed the CRP contract.

Table 1.3. CRP Persistence in Years Based on CRP Categories

CRP Persistence Scenario	Percentage of observations	Persistence in years
Scenario 2	12.90%	5.65
Scenario 3	0.40%	0
Scenario 4	0.41%	1.84
Scenario 5	53.89%	4.07
Scenario 6	15.09%	0
Scenario 7	17.31%	2.27

After CRP contract expiration, two-thirds of the parcels with expired CRP contracts retained the same or similar CRP-based practices for the period of observation, i.e. Scenario 2 and Scenario 5. All the other scenarios consisted of a third of the parcels that converted to another land use within the period of observation; the majority converted to crop production (68.96%). The four major crops that were grown on expired CRP land were soybeans (26.3%), corn (15.5%), winter

wheat (16.3%), and sorghum (10.2%). Other land uses included shrubland (9.72%), fallow (11.31%), hay (7.42%), and development (0.74%), with the rest of the other land use constituting less than 2% of parcels with expired contracts. Over time, we observe the same trend in land use conversion for lands converted after contract expiration, which was most often crop production.

When land-use changes are examined considering parcels that were re-enrolled in CRP, our story changes. We found that for parcels that were re-enrolled in CRP during the observed period, less than 37% of the land use conversion was cropland. For Scenario 3, the two top land uses were hay at 30.48%, followed closely by crop production at 29.5%. In Scenario 4, the primary land-use conversion was to crop production (36.1%), followed closely by shrubland (35.2%). In Scenario 3, reversing the CRP-based practice was immediate, and in Scenario 4, it was at least one year after contract expiration. For CRP contracts that were not renewed, if converted, the most likely land use conversion was to cropland. This accounted for 72.66% of parcels under scenario 6 and 72.81% of parcels under scenario 7, with the former representing land conversion immediately and at least one year after contract expiration for the latter.

5.2 Factors Influencing CRP persistence

We used a Mixed Effect Weibull AFTM to determine which explanatory variables influenced CRP persistence. We estimated average marginal effects (AME) for each explanatory variable, as well. These marginal effects capture the percentage change in CRP persistence per unit change in an explanatory variable, holding all other explanatory variables constant. The scale parameter P for each of the estimated models in Table 1.4 is greater than one, meaning that the probability of maintaining the CRP-based practice increases monotonically with time and supports the assumption that the baseline hazard follows a Weibull distribution. We also find a statistically

significant standard deviation for the random intercept that varies across counties, supporting the use of a Mixed Effect Weibull AFTM clustered at the county level, with a P-value <0.05 .⁶ A positive (negative) coefficient estimates in the Mixed Effect Weibull AFTM show that a covariate increases (decreases) persistence over time. In our case, this means that the covariate prolongs (shortens) CRP persistence.

⁶We also re-estimated the Weibull AFTM using county fixed effects instead of a mixed effect model. We used an LR test to compare the mixed effect Weibull AFTM to a fixed effect Weibull AFTM. The results support the use of mixed effect Weibull AFTM with a p-value <0.01 for the LR test.

Table 1.4. Mixed Effects Weibull Accelerated Failure Time Model (AFTM) Estimation for CRP Persistence

Variables	Model 4A		Model 4B		Model 4C		Model 4D		Model 4E	
	Coeff	% AME	Coeff	% AME	Coeff	% AME	Coeff	% AME	Coeff	% AME
Clay	0.004 (0.004)	0.40	0.004 (0.005)	0.40	0.003 (0.005)	0.30	0.002 (0.005)	0.20	0.002 (0.005)	0.20
Silt	0.003 (0.003)	0.30	0.003 (0.003)	0.30	-0.000 (0.003)	0.00	-0.001 (0.003)	-0.10	-0.001 (0.003)	-0.09
Kw factor	- 1.508** (0.593)	351.77	- 1.502** (0.593)	-77.73	-0.733 (0.620)	-51.95	-0.830 (0.663)	-56.40	-0.783 (0.657)	-54.27
WEI	0.003 (0.002)	0.30	0.003 (0.002)	0.30	0.001 (0.001)	0.10	0.000 (0.001)	0.00	0.000 (0.001)	0.03
Acres	- 0.009** (0.004)	-0.90	- 0.009** (0.004)	-0.90	- 0.010** (0.004)	-1.00	- 0.011** (0.004)	-1.09	- 0.011** (0.004)	-1.05
Acres^2	0.000** * (0.000)	0.00	0.000** * (0.000)	0.00	0.000** * (0.000)	0.00	0.000** * (0.000)	0.00	0.000** * (0.000)	0.00
Class 2	-0.072 (0.130)	-6.95	-0.072 (0.130)	-6.95	-0.163 (0.118)	-15.04	-0.180 (0.137)	-16.47	-0.176 (0.137)	-16.15
Class 3	0.060 (0.131)	6.18	0.059 (0.131)	6.08	-0.094 (0.120)	-8.97	-0.094 (0.139)	-8.97	-0.093 (0.138)	-8.84
Class 4	0.110 (0.138)	11.63	0.109 (0.138)	11.52	-0.092 (0.127)	-8.79	-0.110 (0.144)	-10.42	-0.108 (0.142)	-10.20
Class 5	0.557 (0.441)	74.54	0.556 (0.441)	74.37	0.160 (0.400)	17.35	0.148 (0.373)	15.95	0.151 (0.373)	16.34
Class 6	0.266* (0.154)	30.47	0.265* (0.154)	30.34	0.023 (0.143)	2.33	0.017 (0.158)	1.71	0.022 (0.157)	2.27
Class 7	0.110 (0.203)	11.63	0.110 (0.203)	11.63	-0.056 (0.184)	-5.45	-0.052 (0.201)	-5.07	-0.041 (0.200)	-3.97
Class 2* Acres	0.003		0.003		0.004		0.004		0.004	

Variables	Model 4A		Model 4B		Model 4C		Model 4D		Model 4E	
	Coeff	% AME	Coeff	% AME	Coeff	% AME	Coeff	% AME	Coeff	% AME
	(0.004)		(0.004)		(0.004)		(0.004)		(0.004)	
Class 3* Acres	0.003		0.003		0.004		0.004		0.004	
	(0.004)		(0.004)		(0.004)		(0.004)		(0.004)	
Class 4* Acres	0.005		0.005		0.005		0.005		0.005	
	(0.004)		(0.004)		(0.004)		(0.004)		(0.004)	
Class 5* Acres	0.011		0.011		0.014		0.013		0.012	
	(0.016)		(0.016)		(0.017)		(0.014)		(0.013)	
Class 6* Acres	0.004		0.004		0.004		0.004		0.004	
	(0.004)		(0.004)		(0.004)		(0.004)		(0.004)	
Class 7* Acres	0.006		0.006		0.007		0.007		0.007	
	(0.005)		(0.005)		(0.005)		(0.006)		(0.005)	
Laspeyres crop index	-	-1.09	-	-1.09	-	-1.19	-	-1.19	-	-1.12
	0.011**		0.011**		0.012**		0.012**		0.011**	
	*		*		*		*		*	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
T0=2012	1.941**	596.57	1.942**	597.27	1.887**	559.95	1.852**	537.26	1.873**	550.60
	*		*		*		*		*	
	(0.076)		(0.076)		(0.077)		(0.076)		(0.076)	
T0=2013	1.591**	390.87	1.592**	391.36	1.556**	373.98	1.530**	361.82	1.546**	369.33
	*		*		*		*		*	
	(0.075)		(0.075)		(0.075)		(0.073)		(0.071)	
T0=2014	1.409**	309.19	1.409**	309.19	1.384**	299.08	1.345**	283.82	1.361**	289.87
	*		*		*		*		*	
	(0.075)		(0.074)		(0.070)		(0.071)		(0.070)	
T0=2015	1.205**	233.68	1.204**	233.34	1.197**	231.02	1.152**	216.45	1.168**	221.43
	*		*		*		*		*	
	(0.092)		(0.091)		(0.089)		(0.088)		(0.089)	
T0=2016	1.098**	199.82	1.098**	199.82	1.075**	193.00	1.032**	180.67	1.047**	184.90
	*		*		*		*		*	
	(0.100)		(0.100)		(0.096)		(0.094)		(0.093)	

Variables	Model 4A		Model 4B		Model 4C		Model 4D		Model 4E	
	Coeff	% AME	Coeff	% AME	Coeff	% AME	Coeff	% AME	Coeff	% AME
T0=2017	0.970** * (0.107)	163.79	0.970** * (0.106)	163.79	0.943** * (0.103)	156.77	0.896** * (0.099)	144.98	0.902** * (0.095)	146.46
T0=2018	0.870** * (0.066)	138.69	0.869** * (0.066)	138.45	0.854** * (0.061)	134.90	0.823** * (0.058)	127.73	0.829** * (0.058)	129.13
T0=2019	0.434** * (0.095)	54.34	0.438** * (0.095)	54.96	0.443** * (0.094)	55.74	0.438** * (0.096)	54.96	0.444** * (0.095)	55.89
Mavetemp_10yrlag	0.349** * (0.106)	41.76	0.348** * (0.106)	41.62	0.312** * (0.080)	36.62	0.323** * (0.087)	38.13	0.349** * (0.091)	41.80
Maveprep_10yrlag	-0.003 (0.008)	-0.30	-0.002 (0.008)	-0.20	-0.009* (0.006)	-0.90	-0.011* (0.006)	-1.09	-0.016* (0.008)	-1.54
Mavepdsi_10yrlag	0.035 (0.044)	3.56	0.034 (0.044)	3.46	0.036 (0.040)	3.67	0.044 (0.039)	4.50	0.056 (0.041)	5.80
Nearest wildfire	0.001 (0.000)	0.10	0.001 (0.000)	0.10	0.000 (0.000)	0.00	0.000 (0.000)	0.00	-0.000 (0.000)	-0.01
Megafire	0.452** * (0.118)	57.15	0.451** * (0.117)	56.99	0.409** * (0.111)	50.53	0.386** * (0.111)	47.11	0.355** * (0.109)	42.55
Megafire *Nearest megafire	- 0.001** * (0.000)		- 0.001** * (0.000)		- 0.001** * (0.000)		- 0.001** * (0.000)		- 0.000** * (0.000)	
Megafire damage	9.908** * (0.631)	2008945 .29	0.145 (0.292)	15.60	0.198 (0.331)	21.90	0.023 (0.300)	2.33	0.027 (0.293)	2.72
Percent parcel burnt	-0.001 (0.006)	-0.10	-0.014* (0.008)	-1.39	-0.013 (0.008)	-1.29	-0.013 (0.009)	-1.29	-0.013 (0.009)	-1.27

Variables	Model 4A		Model 4B		Model 4C		Model 4D		Model 4E	
	Coeff	% AME	Coeff	% AME	Coeff	% AME	Coeff	% AME	Coeff	% AME
Megafire damage *Percent parcel burnt	0.006 (0.005)		0.019** *		0.017** (0.007)		0.020** *		0.020** *	
Megafire buffer damage			9.877** *	1947620 .33	9.916** *	2025082 .11	9.368** *	1170667 .63	10.747* **	4650281 .35
Percent buffer burnt			0.025* (0.015)	2.53	0.024 (0.016)	2.43	0.025 (0.017)	2.53	0.024 (0.017)	2.48
Megafire buffer damage* Percent buffer burnt			-0.025* (0.015)		-0.020 (0.016)		-0.026 (0.017)		-0.025 (0.017)	
Perbuffer1000m_crop					-0.001 (0.001)	-0.10				
Perbuffer1000m_developed					-0.000 (0.003)	0.00				
Perbuffer1000m_water					0.004 (0.009)	0.40				
Perbuffer1000m_grass					0.010** *	1.01				
Perbuffer50m_crop							- 0.005** *	-0.50	- 0.005** *	-0.50
Perbuffer50m_developed							(0.001) -0.000 (0.001)	0.00	(0.001) -0.000 (0.001)	-0.03
Perbuffer50m_water							0.010** *	1.01	0.009** *	0.94
Perbuffer50m_grass							(0.003) 0.008** *	0.80	(0.003) 0.008** *	0.80

Variables	Model 4A		Model 4B		Model 4C		Model 4D		Model 4E	
	Coeff	% AME	Coeff	% AME	Coeff	% AME	Coeff	% AME	Coeff	% AME
Land valuation							(0.001)		(0.001)	2.28
Pop estimate									-0.001*	-0.09
									(0.001)	
Constant	-		-		-1.747*		-1.450		-1.959*	
	2.553**		2.552**							
	(1.277)		(1.275)		(0.984)		(1.040)		(1.110)	
Weibull parameter (P)	1.914		1.914		1.921		1.927		1.946	
Variance (constant [County])	0.215**		0.215**		0.126**		0.133**		0.152**	
	*		*		*		*		*	
	(0.071)		(0.071)		(0.041)		(0.044)		(0.059)	
AIC	50533.4		50518.9		49447.8		48283.7		48232.9	
	10		12		95		90		99	
Log likelihood	-		-		-		-		-	
	25227.7		25217.4		24677.9		24095.8		24068.4	
	05		56		47		95		99	
Observations	96042		96042		96042		96005		96005	

Note: Asymptotic standard errors are in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$

% AME change refers to the percentage change in the time of CRP persistence. % AME for interaction terms is incorporated into the individual % AME.

Model 4A in Table 1.4 is our base model and captures the influence of environmental factors, parcel characteristics, crop price index, and contract expiration year. As we move from one subsection to another, we build on the base model by adding more explanatory variables. We did this to determine whether including more explanatory variables improves the model's fit and whether the story changes. Model 4B adds wildfire damage to surrounding land; Model 4C captures the influence of alternative land uses within the 50m buffer; Model 4D estimates the same effects as Model 4C but increases the buffer to 1000m (1 km) for alternative land uses; and Model 4E adds land valuation and population density to the model. AIC and log-likelihood decrease with additional explanatory variables, indicating a better model fit.

5.2.1 Influence of environmental factors, parcel characteristics, crop price index, and contract expiration year on CRP persistence.

In the base model (Model 4A), we see that CRP persistence increases every year the land has been retained in a CRP practice after contract expiration, and the effect was highly significant. The coefficient of the expiration year decreases as we move from $T0 = 2012$ to $T0 = 2020$. The year 2021 is the base year. Looking at the effect of wildfire on CRP persistence, we find that only megafire characteristics had a significant effect on CRP persistence. The closer the megafire was to the parcel, the higher the likelihood of persistence (p-value is 0.01). However, for parcels that were further away from the megafire, CRP persistence decreased for each km the megafire was from the homestead, and it was highly significant. Parcels that were burned by a megafire had a higher CRP persistence level compared to those that were burned by other wildfires. Despite CRP persistence increasing for the percentage of area burned by a megafire event and decreasing for every increase in percentage burned by a smaller wildfire, both effects were insignificant. The

effect of wildfire damage was the same regardless of the percentage of the area burned on the parcel

Regarding climatic factors, we find that as drought severity increases, CRP land is more likely to be converted to other land uses, but the effect was not statistically significant. An increase in the 10-year-moving average lagged temperature increases CRP persistence, while an increase in the 10-year-moving average lagged precipitation decreases CRP persistence. Of the two environmental factors, temperature was the only factor that had a significant relationship with CRP persistence.

For the remaining explanatory variables, the effects on CRP persistence differed. An increase in the two-year lagged moving-average crop price index (Laspeyres price index) resulted in a significant reduction in CRP persistence. None of the physical soil properties influenced CRP persistence in the base model. Based on land capability, the higher the capability class, the greater the CRP persistence relative to Class 1, which was the most suitable for crop production. Irrespective of the acreage, we only observe a significant positive difference between Class 1 and Class 6. As for the influence of erodibility of the land, the higher the Kw-factor, the lower the level of CRP persistence. We observed no significant relationship between the wind erodibility index and CRP persistence in the base model. We found that CRP persistence decreased with acreage as the coefficient on acres was negative, and the effect of acreage was decreasing at an increasing rate ($p\text{-value} < 0.05$, and the coefficient on acres^2 is positive).

Looking at the percentage change average marginal effect (AME) for some significant variables, we find that an increase in acreage by 10 acres decreased CRP persistence time by 9%. For climatic conditions, an increase in the 10-year-moving-average lagged temperature by one

degree Celsius increased CRP persistence time by 42%. An increase in the crop price index by 1% decreased CRP persistence time by 1%. It was interesting that during years with megafires, CRP persistence time increased by 57%, but the effect decreased for every increase in kilometers from a megafire.

5.2.2 Influence of wildfire damage on surrounding land (1000m buffer) on CRP persistence

To further explore the effect of wildfire damage on surrounding land, we estimated Model 4B by including the percentage of burnt area from wildfires and whether megafires or other wildfires caused the damage within a 1000m buffer around the parcel. For every increase in percentage area burned for the surrounding land within a 1000m buffer, CRP persistence increased at a decreasing rate, but the effect was much higher if a megafire caused wildfire damage. Both effects were statistically significant. However, the effect of megafires was the same regardless of the percentage of area burned by megafires.

The size of the coefficients is mostly the same when we compare Model 4B and Model 4A. However, no significant difference was observed for wildfire damage caused by megafires and other wildfires on a parcel. For other wildfires, CRP persistence decreased with an increase in the percentage of area burned by a wildfire, but CRP persistence increased if a megafire caused the damage. At the same time, the sign and significance level remain unchanged for distance to closest wildfire (insignificant) and megafires (-), PDSI drought index (insignificant), parcel characteristics (acreage (-), kw-factor (-), difference between Class 1 and Class 6 (+)), precipitation (insignificant), temperature (+), crop price index (-), and contract expiration year (all +).

The AME for acreage, temperature, crop price index, and megafires in Model 4B is similar to that of Model 4A. An increase in acreage by 10 acres decreases CRP persistence time by 9%. Every increase in the 10-year moving average lagged temperature by 1degree Celsius increases CRP persistence time by 42%, while an increase in the crop price index by 1% decreases CRP persistence time by 1%. As for years in which we had megafires, CRP persistence time increased by 57%. The effect was much higher if a megafire burned the surrounding land (50m buffer), increasing CRP persistence significantly.⁷ Dropping the effect of megafire on a buffer will be misleading, and it may be that megafire on surrounding land plays a crucial role in shaping land management. When examining the data, we find that a higher percentage of buffers around expired CRP parcels are more often burned by wildfires when compared to expired CRP parcels being directly burned by wildfires. An increase in the percentage of area burned on a buffer by 1% increased CRP persistence time by 3%.

5.2.3 Influence of the surrounding land within 50m and 1000m buffers on CRP persistence

We also incorporated the effect of immediate surrounding land use on CRP persistence by creating a 50m and 1000m buffer around each parcel being examined. We added factors examining the influence of alternative land uses within the 50m buffer to Model 4C. CRP persistence decreased with an increase in the percentage of crops on the surrounding land and increased if the parcel is bordered by open water or grassland. We also estimated the same effects when increasing the buffer to 1000m or 1 km, and the findings were relatively the same (see Model 4D in Table 1.4). The only significant land use with the 1000m buffer was grassland, indicating that the higher the

⁷ Dropping the effect of mega wildfire damage on the surrounding land on the model increases the impact of wildfire damage on the parcel, and the AME remains very high, see Model 4A.

percentage of grassland, the more likely the land was to remain under management practices similar to CRP.

There was no change in signs and significance level between Model 4C and Model 4D. In both models, other wildfires no longer influence CRP persistence, but CRP persistence is still higher if a megafire burns the parcel, and it increases as the percentage of the parcel burned increases. Megafire damage in the surrounding 1000m buffer still increases CRP persistence irrespective of the percentage area burned, and it is significant at the 1% level. Different from the prior models, an increase in the 10-year moving average of lagged precipitation decreases CRP persistence. In the case of the land capability class, signs have changed for some, but none are statistically significant. The percentage of silt switched signs from positive to negative, but the effect on CRP persistence remains insignificant. Kw-factor is no longer statistically significant. We observe similar results for other explanatory variables, i.e., distance to closest wildfire (insignificant) and megafires (-), PDSI drought index (insignificant), parcel characteristics (acreage (-)), temperature (+), crop price index (-), and contract expiration year (all +).

For Model 4C and Model 4D, the AME for acreage and crop price index is slightly higher than those of Model 4A and Model 4B. An increase in acreage by 10 acres increases CRP persistence time by 10% and decreases CRP persistence time by 1% for an increase in the crop price index by 1%. The 10-year moving average lagged temperature had a slightly lower effect on CRP persistence time; an increase in the 10-year moving average lagged temperature by 1-degree Celsius increased CRP persistence time by 37% in Model 4C and 38% in Model 4D. An increase in the 10-year moving average lagged precipitation by a millimeter decreased CRP persistence time by 1% for both Model 4C and Model 4D, which was insignificant for Model 4A and 4B.

Years in which we had megafire increased CRP persistence time by 51% in Model 4C and 47% in Model 4D, which was lower than the other two prior models. Megafire damage on the buffer still had a highly positive and significant effect on CRP persistence.

For a 50 m buffer of surrounding land (Model 4D), an increase in the percentage of crop land by 1% for the surrounding land decreased CRP persistence time by 0.50%. In comparison, a 1 per cent increase in open water increased CRP persistence time by roughly 1%, and an increase in the percentage of grassland by unit increased CRP persistence time by 0.80%. In Model 4C, when the buffer was increased to 1000m, only the percentage of grassland had a significant effect. An increase in the percentage of grassland by 1% increased CRP persistence time by 1%.

5.2.4 Influence of land valuation and population density on CRP persistence

Our final model, Model 4E, included land valuation and population density to better control for influences from market and development factors, and both variables were significant. We use 50m buffer for surrounding land use. Increases in mean land valuation ($\frac{\text{CRP rental rates}}{\text{Land rental rates}}$) increased CRP persistence and an increase in population density decreased CRP persistence. The effect of megafires was still significant. Parcels close to megafires had a higher CRP persistence, and so did landowners who had a megafire burn on the expired CRP parcel or surrounding land. Although the sign of the nearest wildfire distance switched sign from positive to negative, it was statistically insignificant, like the other models. An increase in the percentage of crops on the surrounding land still decreased CRP persistence, and an increase in the percentage of open water and grassland increased CRP persistence. We observe similar findings for the other explanatory variables as Model 4C, i.e., distance to closest megafires (-), PDSI drought index (insignificant), parcel

characteristics (all insignificant except acreage (-)), precipitation (-), temperature (+), crop price index (-), and contract expiration year (all +).

The AME for Model 4E shows that acreage and crop price index are similar to those in Model 4D. CRP persistence time increased by 1% for one acre increase in acreage and decreased by 1% for an increase in the crop price index by 1%. 10-year moving average lagged precipitation by a millimeter still had a negative effect and decreased CRP persistence time by 2%, and the 10-year moving average lagged temperature by 1-degree Celsius increased CRP persistence time by 42%. AME for the megafire variable was slightly lower than Model 4D; in years in which we had megafire, CRP persistence time increased by 43%. As for megafire damage on the buffer, CRP persistence time increased, and the effect was highly significant. The effect of a 50m buffer surrounding land use was similar to Model 4D. An increase in the percentage of crop land by 1% decreased CRP persistence time by 0.50%, a 1 per cent increase in open water increased CRP persistence time by about 1%, and an increase in the percentage of grassland by 1% increased CRP persistence time by 0.80%. An increase in the land valuation ratio by a unit increased CRP persistence time by 2%. The effect of population was much smaller; for every increase of 1000 people in the county, CRP persistence time decreased by less than 1%.

5.3 Robustness Checks

We carried out several robustness checks that are presented in Table 5. Model 4E is the base for these robustness checks because it fully captures all significant effects, as well as controlling for both unobserved geographical heterogeneity and trends in prices and weather. In Model 5A, we estimate the base model as a Fixed Effects model at the county level. For Models 5B and 5C, we replace the original crop price index with a one-year-lagged and a two-year-lagged crop price

index, respectively, instead of using a two-year-lagged moving average crop price index; in Model 5D we replace the PDSI drought index with the SPI drought index, while in Model 5E we replace the PDSI drought index with the Z-index. Model 5F replaces the 10-year lagged moving average for weather variables and drought with a five-year lagged moving average value, and Model 5G replaces it with a one-year lagged moving average. Model 5H drops CRP parcels that were reenrolled to CRP to determine if the story changes when only considering those expiring CRP parcels that are never re-enrolled. In the Appendix, Appendix Table A.1, we examine the interaction between wildfire experience and the acreage of expired CRP parcels on CRP persistence, and in Appendix Table A.2, we determine the effect of including wildfire and percent grassland interactions.⁸

⁸ We also conducted a robustness check by estimating a model without expired CRP parcels that had only been burned by a megafire on the buffer, but we did not have enough observations to estimate the model.

Table 1.5. Robustness Checks for Mixed Effects Weibull Accelerated Failure Time Model (AFTM)

Variables	Model 5A Coeff	Model 5B Coeff	Model 5C Coeff	Model 5D Coeff	Model 5E Coeff	Model 5F Coeff	Model 5G Coeff	Model 5H Coeff
Clay	0.003 (0.002)	0.002 (0.005)	0.002 (0.005)	0.002 (0.005)	0.003 (0.005)	0.002 (0.004)	0.001 (0.004)	0.003 (0.005)
silt	-0.000 (0.002)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	0.000 (0.003)
Kw factor	- 0.892*** (0.273)	-0.896 (0.726)	-0.726 (0.662)	-0.748 (0.663)	-0.819 (0.658)	-0.623 (0.592)	-0.882 (0.642)	-1.282** (0.596)
WEI	0.000 (0.001)	0.000 (0.002)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	-0.001 (0.002)
Acres	- 0.011*** (0.003)	-0.012** (0.005)	-0.011** (0.004)	-0.010** (0.004)	-0.010** (0.004)	-0.010*** (0.003)	-0.007** (0.003)	-0.010** (0.004)
Acres^2	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Class 2	-0.178 (0.122)	-0.178 (0.150)	-0.183 (0.137)	-0.175 (0.138)	-0.183 (0.132)	-0.208** (0.104)	-0.171 (0.106)	-0.192 (0.131)
Class 3	-0.090 (0.122)	-0.080 (0.152)	-0.102 (0.138)	-0.093 (0.139)	-0.097 (0.133)	-0.144 (0.105)	-0.103 (0.107)	-0.096 (0.134)
Class 4	-0.110 (0.125)	-0.094 (0.157)	-0.118 (0.143)	-0.107 (0.144)	-0.111 (0.137)	-0.146 (0.112)	-0.093 (0.111)	-0.078 (0.137)
Class 5	0.138 (0.418)	0.219 (0.402)	0.124 (0.392)	0.154 (0.373)	0.128 (0.365)	-0.039 (0.338)	0.105 (0.291)	0.275 (0.478)
Class 6	0.015 (0.127)	0.051 (0.174)	0.016 (0.157)	0.023 (0.158)	0.020 (0.152)	-0.056 (0.119)	-0.017 (0.119)	0.012 (0.148)
Class 7	-0.044 (0.184)	-0.002 (0.223)	-0.060 (0.201)	-0.041 (0.200)	-0.035 (0.198)	-0.112 (0.167)	-0.007 (0.156)	0.110 (0.220)

Variables	Model 5A Coeff	Model 5B Coeff	Model 5C Coeff	Model 5D Coeff	Model 5E Coeff	Model 5F Coeff	Model 5G Coeff	Model 5H Coeff
Class 2* Acres	0.005 (0.003)	0.005 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.003)	0.002 (0.003)	0.004 (0.004)
Class 3* Acres	0.005 (0.003)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.003)	0.002 (0.003)	0.003 (0.004)
Class 4* Acres	0.006* (0.003)	0.006 (0.005)	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	0.005 (0.003)	0.002 (0.003)	0.003 (0.004)
Class 5* Acres	0.013 (0.017)	0.013 (0.015)	0.013 (0.014)	0.012 (0.013)	0.012 (0.013)	0.014 (0.012)	0.008 (0.010)	0.006 (0.020)
Class 6* Acres	0.004 (0.003)	0.004 (0.005)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.003)	0.002 (0.003)	0.003 (0.004)
Class 7* Acres	0.007 (0.004)	0.007 (0.006)	0.007 (0.006)	0.007 (0.005)	0.007 (0.005)	0.006 (0.004)	0.004 (0.004)	0.004 (0.006)
T0=2012	1.883*** (0.030)	1.654*** (0.089)	1.937*** (0.072)	1.866*** (0.077)	1.880*** (0.074)	2.202*** (0.081)	2.205*** (0.054)	1.734*** (0.074)
T0=2013	1.557*** (0.028)	1.311*** (0.079)	1.684*** (0.073)	1.537*** (0.072)	1.554*** (0.070)	1.848*** (0.081)	1.693*** (0.052)	1.491*** (0.066)
T0=2014	1.371*** (0.028)	1.228*** (0.081)	1.483*** (0.063)	1.352*** (0.071)	1.364*** (0.069)	1.645*** (0.059)	1.577*** (0.062)	1.167*** (0.066)
T0=2015	1.174*** (0.033)	1.062*** (0.096)	1.273*** (0.082)	1.162*** (0.089)	1.169*** (0.088)	1.396*** (0.065)	1.376*** (0.072)	0.998*** (0.072)
T0=2016	1.052*** (0.031)	0.964*** (0.099)	1.138*** (0.089)	1.039*** (0.092)	1.051*** (0.093)	1.247*** (0.078)	1.225*** (0.072)	0.924*** (0.088)
T0=2017	0.903*** (0.031)	0.836*** (0.100)	0.985*** (0.099)	0.898*** (0.096)	0.899*** (0.093)	1.016*** (0.094)	1.012*** (0.066)	0.858*** (0.078)
T0=2018	0.830*** (0.027)	0.780*** (0.061)	0.928*** (0.060)	0.826*** (0.059)	0.827*** (0.058)	0.894*** (0.050)	0.817*** (0.046)	0.634*** (0.059)
T0=2019	0.439*** (0.034)	0.369*** (0.104)	0.531*** (0.095)	0.438*** (0.096)	0.436*** (0.095)	0.467*** (0.081)	0.391*** (0.088)	0.245*** (0.080)

Variables	Model 5A Coeff	Model 5B Coeff	Model 5C Coeff	Model 5D Coeff	Model 5E Coeff	Model 5F Coeff	Model 5G Coeff	Model 5H Coeff
Nearest wildfire	-0.000 (0.000)	-0.000 (0.001)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.001** (0.000)	0.000 (0.000)	0.000 (0.000)
Megafire	0.355*** (0.022)	0.453*** (0.101)	0.298** (0.133)	0.359*** (0.107)	0.336*** (0.110)	0.421*** (0.116)	0.550*** (0.104)	0.308*** (0.096)
	-	-	-	-	-			
Megafire *Nearest megafire	0.000*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.001*** (0.000)	-0.000** (0.000)	-0.000*** (0.000)
Megafire damage	-0.169 (0.302)	0.170 (0.337)	0.107 (0.280)	0.119 (0.308)	0.159 (0.305)	0.469** (0.207)	0.427 (0.263)	0.345 (0.357)
	-							
Percent parcel burnt	0.013*** (0.004)	-0.014 (0.009)	-0.013 (0.008)	-0.013 (0.009)	-0.013 (0.009)	-0.011* (0.006)	-0.009 (0.007)	-0.016** (0.008)
Megafire damage *Percent parcel burnt	0.021*** (0.006)	0.019** (0.008)	0.018** (0.007)	0.017** (0.007)	0.017** (0.007)	0.010* (0.006)	0.009 (0.006)	0.016** (0.007)
		11.659**		10.369**				
Megafire buffer damage	7.492*** (0.156)	* (0.597)	9.645*** (0.494)	* (0.531)	9.256*** (0.500)	6.751*** (0.462)	6.875*** (0.363)	9.204*** (0.484)
Percent buffer burnt	0.024*** (0.009)	0.026 (0.018)	0.024 (0.017)	0.025 (0.017)	0.024 (0.017)	0.020 (0.014)	0.021 (0.014)	0.025* (0.015)
	-							
Megafire buffer damage* Percent buffer burnt	0.034*** (0.010)	-0.022 (0.018)	-0.021 (0.017)	-0.020 (0.017)	-0.020 (0.017)	-0.007 (0.014)	-0.006 (0.014)	-0.015 (0.014)
	-	-	-	-	-			
Perbuffer50m_crop	0.005*** (0.000)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.005*** (0.001)
Perbuffer50m_developed	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.001 (0.001)
Perbuffer50m_water	0.009*** (0.003)	0.010*** (0.003)	0.010*** (0.003)	0.009*** (0.003)	0.009*** (0.003)	0.008*** (0.003)	0.009*** (0.003)	0.007** (0.003)

Variables	Model 5A Coeff	Model 5B Coeff	Model 5C Coeff	Model 5D Coeff	Model 5E Coeff	Model 5F Coeff	Model 5G Coeff	Model 5H Coeff
Perbuffer50m_grass	0.008*** (0.000)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.007*** (0.001)	0.006*** (0.001)	0.008*** (0.001)
Land valuation	0.030*** (0.003)	0.028*** (0.009)	0.030*** (0.011)	0.022** (0.009)	0.024*** (0.009)	0.022** (0.009)	0.007 (0.007)	0.025*** (0.008)
Pop estimate	-0.013** (0.005)	-0.001* (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.000)	-0.002** (0.001)	0.000 (0.001)	-0.001 (0.001)
Laspeyres crop index	0.011*** (0.000)			0.011*** (0.001)	0.011*** (0.001)	-0.009*** (0.001)	-0.012*** (0.001)	-0.011*** (0.001)
Mavetemp_10yrlag	0.382*** (0.029)	0.452*** (0.108)	0.300*** (0.087)	0.353*** (0.091)	0.352*** (0.093)			0.347*** (0.086)
Maveprep_10yrlag	0.004 (0.004)	-0.019** (0.009)	-0.014 (0.010)	-0.015* (0.009)	0.024*** (0.007)			-0.013 (0.008)
Mavepdsi_10yrlag	-0.010 (0.018)	0.081* (0.046)	0.040 (0.043)					0.032 (0.043)
Mavespi_10yrlag				0.351 (0.400)				
MaveZ-index_10yrlag					0.405*** (0.151)			
Lag1_Crop_index		- 0.010*** (0.001)						
Lag2_Crop_index			- 0.009*** (0.001)					
Mavetemp_5yrlag						-0.131** (0.065)		
Maveprep_5yrlag						0.043***		

Variables	Model 5A Coeff	Model 5B Coeff	Model 5C Coeff	Model 5D Coeff	Model 5E Coeff	Model 5F Coeff	Model 5G Coeff	Model 5H Coeff
Mavepdsi_5yrlag						(0.005) 0.050 (0.032)		
Mavetemp_1yrlag							-0.386*** (0.039)	
Maveprep_1yrlag							-0.007*** (0.001)	
Mavepdsi_1yrlag							0.034** (0.016)	
Constant		-3.133** (1.336)	-1.666 (1.084)	-2.002* (1.074)	-1.654 (1.053)	-0.213 (0.875)	6.851*** (0.526)	-1.941* (1.016)
County Fixed Effects	Yes	No	No	No	No	No	No	No
Drop re-enrolled expired CRP Parcels	No	No	No	No	No	No	No	Yes
Weibull parameter (P)	1.964	1.761	1.925	1.944	1.960	2.314	2.382	2.020
Variance (constant [County])		0.205** (0.081)	0.178** (0.085)	0.143** (0.058)	0.124*** (0.034)	1.043*** (0.201)	0.253*** (0.055)	0.170*** (0.059)
AIC	37817.56 1	48877.40 8	48278.15 0	48237.27 3	48178.65 9	46754.071	46108.769	43387.020
Log likelihood	18757.78 0	24390.70 4	24091.07 5	24070.63 6	24041.33 0	23329.036	23006.384	21645.510
Observations	96005	96005	96005	96005	96005	96005	96005	76454

Note: Asymptotic standard errors are in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$.
We have not included the constant term for the counties in a fixed-effects model.

5.3.1 Fixed effects specification robustness check

Model 5A shows the results of a Fixed Effects Weibull AFTM at the county level. The results are not very different from Model 4E. We observe that CRP parcels burned by other wildfires significantly reduce CRP persistence. In contrast, CRP persistence increases if a megafire burns the surrounding land, but the effect decreases for every increase in the percentage area burned. The PDSI drought index still does not influence CRP persistence, and surrounding land use continues to influence it. Precipitation has no effect on CRP persistence, and an increase in the Kw factor significantly reduces CRP persistence. Using a fixed-effect Weibull AFTM captures county effects but does not control for random variation between counties, which is captured by the Mixed Effects Weibull AFTM.

5.3.2 Robustness check on the measure of crop price index

We examine the indicator used for the crop price index. In Models 5B and 5C, we test the use of a one-year lagged and a two-year lagged crop price index instead of using a two-year lagged moving average crop price index. We observe similar signs and magnitudes for the coefficients between the models for the different specifications of the crop price index. An increase in the crop price index had a negative effect on CRP persistence, irrespective of the measure of the crop price index used. However, using a one-year lag in the crop price index changed the significance levels of some variables, with some switching from p-values of 0.01 to 0.05, but the effects of wildfires and surrounding land use on CRP persistence remain unchanged. However, an increase in drought by one degree Celsius reduces CRP persistence, which was not previously observed. The one-year lag may be introducing noise and inaccuracy in the model estimation, or it may not be capturing as much information, as some of the effects disappear when a two-year crop price index lag is used. When we use a two-year lagged crop price index, the effect of precipitation and population

density on CRP persistence becomes insignificant. A two-year lagged moving average crop price index can potentially reduce noise and capture trends that may not be captured using a lagged or a two-lagged crop price index (Zakamulin 2017; Robert Lacoste 2010). Taking the average of the two prices shows the size and direction of the price change over time.

5.3.3 Robustness checks on the choice of drought indicator

In Model 5D, we replaced the PDSI drought index with the SPI drought index measure, both of which measure long-term drought. We observe similar signs and significance for most of the explanatory variables. Although the sign on the coefficient is the same, the effect of population density on CRP persistence is insignificant compared to our final Mixed Effects Weibull AFTM (Model 4E). Using the SPI drought index measure increases the coefficient, but the effect remains positive and still statistically insignificant. We also rerun the model using the Z-index (Model 5E) and found almost similar results to Model 4E for the effect of the explanatory variable on CRP persistence. However, we observed a larger coefficient estimated on the Z-index (short-term drought index), and the effect of drought was highly significant when the Z-Index was used. As the severity of short-term drought increases, it is more likely that the land will be converted from a CRP-based practice to another land use. Positive values represent moisture levels above normal moisture conditions, and the negative values represent moisture levels below normal conditions. In our case, when the Z-index is negative, then there is a short-term drought, and the more negative it is, the more severe the drought. Irrespective of the drought indicator chosen, the effects of wildfire and surrounding land use remained unchanged. The different measures of drought have different input parameters used to calculate the index, and this may be captured by the different effects. PDSI and SPI drought index measures long-term drought, and the Z-index is a derivative of PDSI and captures short-term droughts. This may explain the difference in significance levels

for the drought indices. It may be that a short-term drought influences land management decisions, and a reduction in CRP persistence is a way of coping with the new threat.

5.3.4 Robustness check on measures of climatic conditions

In Model 5F and Model 5G, we capture climatic conditions, i.e., temperature, precipitation, and PDSI, as a five-year lagged moving average and a one-year lagged value rather than the 10-year moving average. Using a five-year lagged moving average for climatic conditions changes the signs and significance levels of some of the climatic effects on CRP persistence compared to the prior mixed-effect Weibull AFTMs estimated (Model 4E). An increase in temperature decreases CRP persistence, and an increase in precipitation increases CRP persistence, while the effect of drought on CRP persistence remains insignificant. As for the one-year lagged measures, the effects of temperature, precipitation, and drought are all negative, i.e., an increase in any of them decreases CRP persistence. The one-year lagged captures “noise” in weather, while the moving averages may be capturing a signal or patterns in weather. That is, the one-year lag to the farmer is likely more uncertain (Ramsey et al. 2021). A ten-year lagged moving average is sufficient to start observing short-term trends in environmental factors. (National Center for Atmospheric Research Staff (Eds) 2014). This indicates that farmers are likely to respond to short-term weather changes differently from longer-term patterns. However, the effects of megafires and surrounding land on CRP persistence remain unchanged across these models.

5.3.5 Robustness check when considering only expired CRP parcels that never reenroll

In Model 5H, we show the estimated results for only expired CRP lands that were not re-enrolled, and the results are not much different to Model 4E. However, in Model 5H, the underlying story remains the same, megafire on a parcel or surrounding land increased CRP persistence, while other

wildfires on a parcel reduced CRP persistence. The effect of surrounding land use on CRP persistence remains unchanged. We also observe that precipitation is no longer significant, and that the Kw factor has a significant negative effect on CRP persistence.

5.3.6 Robustness check when including interactions between wildfire experience and the acreage

We also conducted a robustness check on including interactions between wildfire experience and the acreage of expired CRP parcels; see Appendix Table A.1 in the appendix. To do so, we determined six quantile for the sizes of expired CRP parcels that were burnt by wildfire or surrounding land⁹: 5th (1.55), 10th (3.32), 25th (7.92), 50th (20.76), 75th (53.57), and 90th (110.03). The values in brackets represent the acreage for a parcel at a given quantile. In the first model, we used the first percentile values, and we grouped observations into two groups: a parcel =1 if Acreage $\geq$ 1.55 and 0 otherwise and followed the same procedure for the rest of the percentiles, resulting in six models. The effect and significance of the effects of wildfires on CRP persistence depend on how observations are grouped. However, the underlying story remains consistent: if there is megafire damage on an expired CRP parcel, CRP persistence decreases, but the effects of a megafire on the surrounding land result in an increase in CRP persistence, which is much larger in magnitude. That is, the impact of megafires on the surrounding land has a dominating effect on CRP persistence. Interestingly, at an acreage above 110 acres, CRP persistence increases if a megafire burns the expired CRP parcel, see Appendix Table A.1, Model F. In addition, the effect of other wildfires is always smaller than that of megafires, either on the parcel or the surrounding land, and in most cases, CRP persistence is not affected by other wildfires.

⁹We could not estimate the other percentiles because of collinearity issues.

5.3.7 Robustness check to inclusion of interaction between megafire damage and the percent of grassland on the 1000m buffer

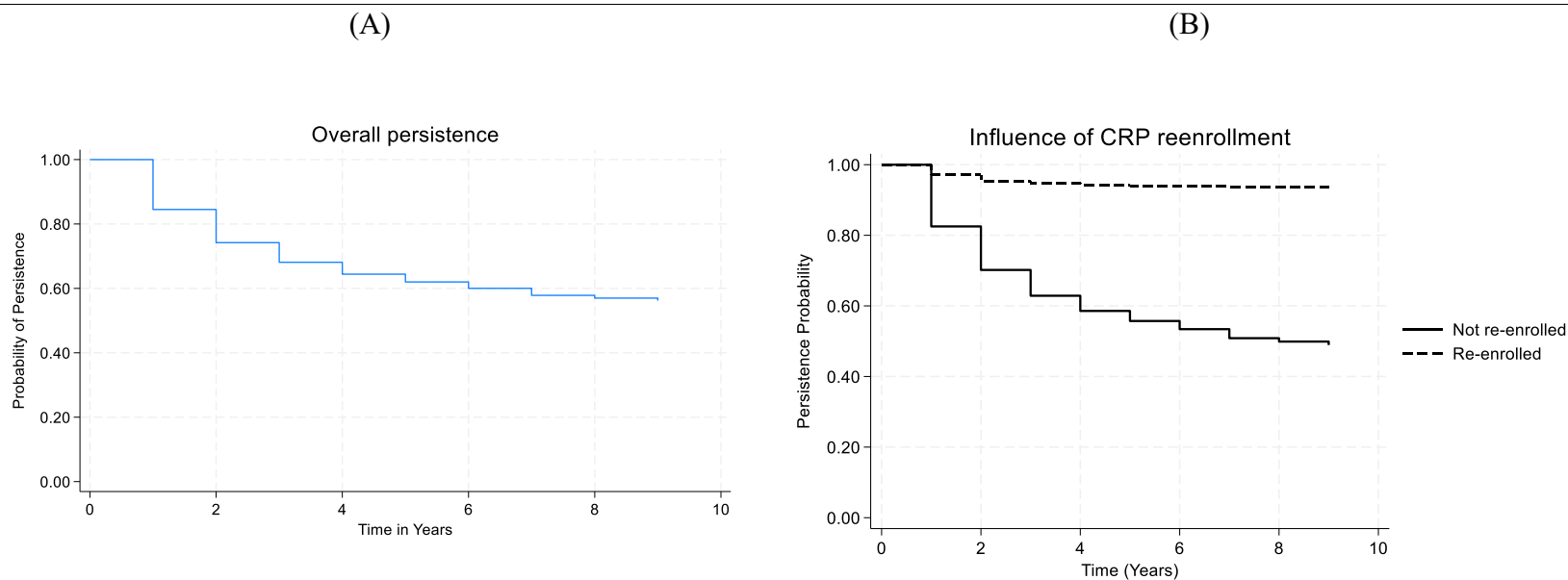
In Appendix Table A.2 in the appendix, we show the results of including an interaction between megafire damage and the percentage of grassland on the 1000m buffer in Model 4E. We observe that megafires on the parcel or on surrounding land continue to increase CRP persistence, and it is negative in the other models but often insignificant. The effects of drought and surrounding land use on CRP persistence remain unchanged. Also, parcels whose surrounding land was burned by a megafire were more likely to have a higher CRP persistence level if the parcel was mostly surrounded by grassland. The CRP persistence level increased for each increase in the percentage of grassland.

In general, regardless of the chosen robustness check, our story remains the same. Megafires on expired CRP parcels often have a negative but insignificant influence on CRP persistence, while megafires on surrounding land increase CRP persistence, being a dominant influence. Long-term drought effects had no significant effect on CRP persistence, whereas surrounding land use had a significant effect on CRP persistence, especially the presence of cropland. CRP persistence increased with a percentage increase in grassland and open water of the surrounding land and decreased with a percentage increase in cropland.

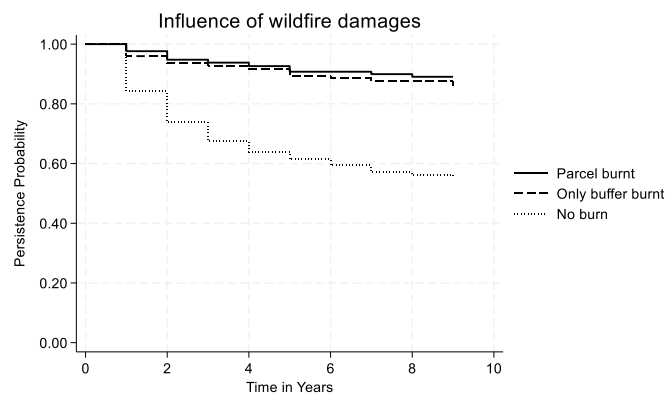
5.4 Probability of CRP persistence across years after contract expiration based on drought and wildfire events.

In this section, we look at the probability of CRP persistence over time when influenced by wildfire and drought. We do this by plotting Kaplan-Meier curves that estimate survival rates (or CRP persistence) over time in Figure 1.3 (Sullins et al. 2021). The period of observation for our dataset is 9 years (given a base year). Overall (Figure 1.3A), the probability of persistence decreases over time, decreasing to less than 60 percent after 8 years. The largest marginal increases in CRP reversals to other land management uses occur during the first two years of contract expiration (Figure 1.3A). In the second year after contract expiration, the probability of persistence was 74% and was 56% by the 9th year. In Figure 1.3B, we examine CRP persistence between observations in two groups: those landowners who re-enrolled CRP parcels and those landowners who did not re-enroll. We find, on average, a higher probability of CRP persistence in the former group over time. In the 9th year, the probability of CRP persistence is 94% for land that is reenrolled back to CRP and 49% for land that is not reenrolled back to CRP.

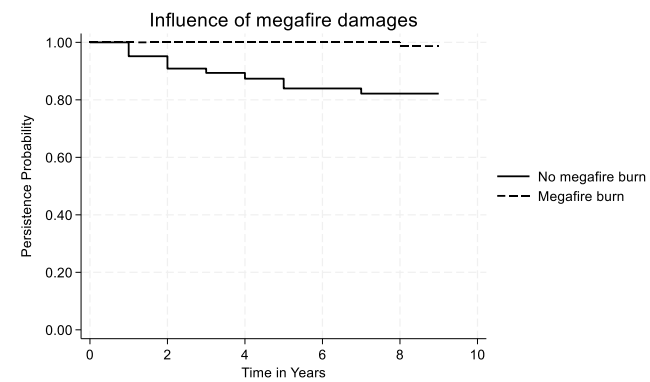
Figure 1.3. Probability of CRP Persistence Overall, and Based on Grouped Data, i.e. CRP Re-enrollment, Type of Wildfire Damage, Drought Conditions, and Surrounding Land Use. (A) The probability of CRP persistence over time under normal environmental conditions. (B) distinguishes the probability of CRP persistence over time between landowners who re-enrolled CRP parcels and those landowners who did not re-enrol. (C) shows CRP persistence probability over time for those that had only CRP parcel burned by any wildfire (Parcel burn), those that had only surrounding land burned by any wildfires and not their CRP expired parcel (Only buffer), and those that never had wildfires on their CRP expired parcels or surrounding land (no burn). (D) compares CRP persistence probability for those parcels that had megafires on their CRP expired parcels or surrounding land and those that only had other wildfires. (E) shows CRP persistence probability across various PDSI classes. (F) compares CRP persistence probability across various percentages of grassland for surrounding land use within a 50m buffer of the expiring CRP parcel. (G) displays CRP persistence probability at various percentages of cropland for surrounding land use within a 50m buffer of the expiring CRP parcel



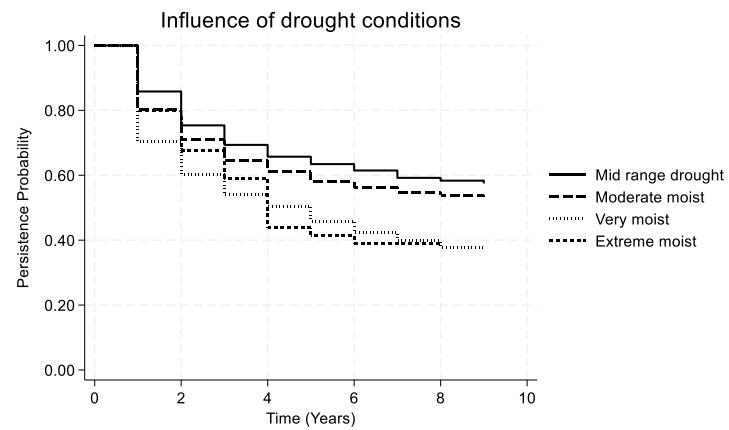
(c)



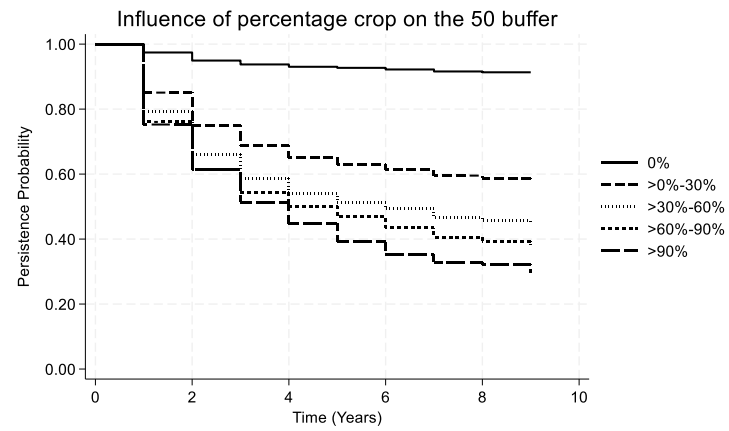
(D)



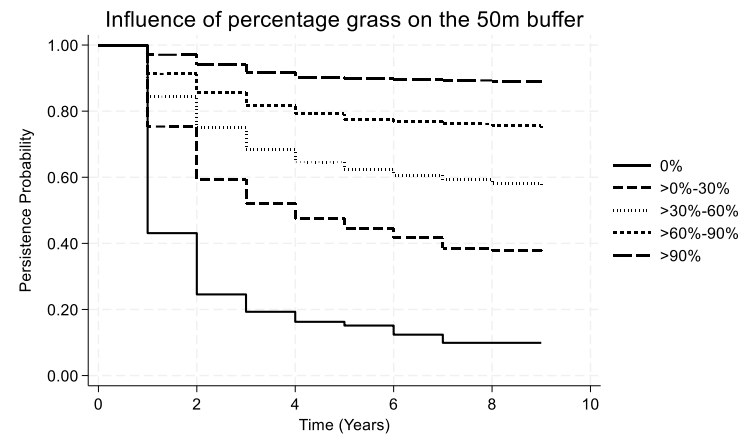
(E)



(F)



(G)



To study the impact of wildfire damage on the probability of CRP persistence, we grouped observations into three groups. Those landowners that had their CRP parcel burned by any wildfire (Group 1), those that had only surrounding land burned by any wildfires and not their CRP expired parcel (Group 2), and those that never had wildfires on their CRP expired parcels or surrounding land (Group 3). The influence of wildfire on CRP persistence across these three groups is shown in Figure 1.3C. We observe higher CRP reversal within the first two years for all three groups. The probability of CRP persistence is higher for landowners who have had their CRP parcel burnt by any wildfires and decreases slowly with time. The probability of persistence is 94% in the second year and 88% in the 9th year. However, we do not observe much difference in the probability of CRP persistence when the surrounding land is burned by wildfire compared to when wildfire damage occurs on the expired CRP land. The probability of CRP persistence is 94% in the 2nd year and 86% in the 9th year. As for those expired CRP lands that had no wildfire damage on the land and surrounding land, the probability of CRP persistence was much lower and had a higher rate of CRP reversal during the first four years compared to the prior groups. The probability of CRP persistence was 74% in the 2nd year and 55% in the 9th year. It was interesting to see that even when comparing the 1st year CRP persistence rate for Group 3 and the 9th year CRP persistence rate for Group 1 or Group 2, it was always higher for the latter. However, when we focus only on the effects of megafire damage (see Figure 1.3D), megafires dominate the effects of CRP persistence. CRP persistence is 100% for the first 8 years and declines only to 98% in the 9th year.

For drought, we looked at CRP persistence based on different classes of drought. We computed the average PDSI score for the period of observation and had four classes for PDSI based on our data: mid-range drought, moderately moist, very moist, and extremely moist classes. The probability of CRP persistence was always higher for expired CRP parcels that were in the

mid-range drought category than for expired CRP parcels that were in the moderately moist conditions category (Figure 1.3E). Expired CRP parcels that were in the very moist condition category had the lowest probability of CRP persistence in the first 3 years after contract expiration, and afterwards, the probability of CRP persistence was much lower for parcels that were in the extremely moist condition category. When we compare the two extreme drought conditions, the probability of CRP persistence is 75% in the 2nd year and 58% in the 8th year for parcels in the mid-range drought and for those parcels allocated in extreme moist conditions, CRP persistence is lower at 67% in the 2nd year and 38% in the 8th year.

Lastly, we examine the influence of surrounding land use within a 50m buffer of the expiring CRP parcel on CRP persistence. We grouped observations into five groups based on the percentage of crops or grassland within the 50m buffer of the surrounding land, i.e., 0.01-30, 30.01-60, 60.01-90, and greater than 90 percent. We found that CRP persistence was higher on land with 90% or more of their surrounding land in grassland, see Figure 1.3F. In the 1st year, these lands had a 97% probability of retaining CRP-based practices and 89% in the 9th year. However, for parcels with little to no grassland in their surrounding area, the probability of retaining CRP-based practices after contract expiration was much lower: 43% in the 1st year and 10% in the 9th year. For crops, we observe less disparity between the classes (Figure 1.3G). Expired CRP parcels that had 0% of their surrounding land in crop production had a higher CRP persistence. The probability of retaining the CRP-based practice was 97% in the first year, and by the 9th year, the land still had a high probability of persistence at 91%. However, for those CRP parcels that had more than 90% of their surrounding land in crops, the probability of persistence was very low compared to the other classes. It was 75% in the 1st year and 29% in the 9th year.

5.6 Discussion

The rate of CRP persistence, or the percentage of parcels examined that exhibited some level of CRP persistence, from 2012 to 2021 in Kansas was 67%, with most CRP reversals occurring during the first two years after CRP contract expiration. Recall that we can only capture that CRP practices remained within grassland-based practices based on the data utilized for this study between 2012 and 2021. Land use conversions captured changes in land use to another cover, such as crop production or development. In the literature, CRP persistence ranges between 41 and 67%, with most of these studies carried out in the Great Plains (Hendricks and Er 2018; Sullins et al. 2021; Barnes et al. 2020; Bigelow et al. 2020; Vandever et al. 2023). As time progresses, the probability of CRP persistence decreases, and this has also been evidenced in other studies (Sullins et al. 2021; Barnes et al. 2020).

On average, CRP-based practices or similar land management remained on an expired CRP parcel for 3.3 years after contract expiration, with most studies finding CRP reversal happening within the first 5 years (Sullins et al. 2021; Bigelow et al. 2020; Vandever et al. 2023; Aragon et al. 2025). In fact, we find on the margin that many of these actually happen within the first two years after contract expiration. However, landowners who intend to re-enroll their land into the CRP tend to have a higher CRP persistence rate than those who do not, being 5 years and 3 years, respectively, and to our knowledge, there is no study in the literature that has documented this. Most expired CRP parcels converted to crop production, with the four major crops being corn, wheat, sorghum, and soybeans. In the literature, the main land use that grasslands or expired CRP parcels were reverted to was dryland crops (Barnes et al. 2020; Morefield et al. 2016; Lark et al. 2015; Caldas et al. 2016; Roberts and Lubowski 2007; Bigelow et al. 2020; Vandever et al. 2023). Growing crops on expired CRP parcels can undo the environmental benefit achieved as it involves

clearing off grassland cover (Dayer et al. 2018). However, if the expired CRP parcel was going to be re-enrolled, it was less likely to be converted to crop production. This finding is similar to an earlier study by Barnes et al. (2020). Thus, even if contract renewal was not immediate, keeping in touch with farmers during transitions between contract expiration and renewal is critical if the goal is to maintain conservation benefits on the land longer term, given competition for program enrollment. While a farmer may not be able to enroll the land immediately the following enrollment period, if they can do so within a limited number of years, conservation benefits may be maintained in the interim, further increasing the long-term value of the CRP.

To understand what drives CRP persistence, we looked at a number of factors, including wildfires. Megafires had a major impact on CRP persistence. We defined a megafire as a wildfire that burned 100,000 acres or more. Megafires have a lasting effect on landowners' wildfire risk and perception compared to other wildfires, which have smaller effects (Caldas et al. 2026). However, wildfire risk decreased with an increase in the distance from the megafire. Other wildfires have less impact because they often burn significantly less than 100,000 acres. Landowners may recover more quickly from such events, and there are benefits, such as improved grazing, that may result from it. Expired CRP parcels that were burned by a megafire were more likely to retain the CRP-based practice after contract expiration. Even for those parcels that had the surrounding land destroyed by a megafire (1000m buffer surrounding land), the landowner was still more likely to retain the CRP-based practice. But if the parcel and surrounding land were not burned by a megafire, CRP persistence rate was much lower. This may be explained by the negative coefficient in the distance to a megafire in a given year. The further the parcel was from a megafire, the less likely of having CRP persistence.

Our results do not imply that megafires lead to CRP persistence, only that megafires influence CRP persistence if the surrounding land is burned by a megafire. A megafire can have a very significant impact on a landowner's or producer's operation, which may take time to recover from. As the landowner rebuilds, the land may be used for land uses that require less infrastructure investment, such as hunting or grazing, which may warrant retaining the land under a CRP-based practice, in our case, grassland. Land takes time to recover from a megafire, and by maintaining the land longer, plant health and productivity improve (Texas A&M Forest Service 2026). Furthermore, as mentioned earlier, the influence of megafire events most often occurred on CRP parcels that were predominantly surrounded by grassland. We find that, on average, the expired CRP parcels that were burned by a megafire or surrounding land or both had, on average, about 73% of the surrounding land (1000m) consisting of grasslands and 17% consisting of crops. Conversion of such land to another use, such as crop production, may be too high an opportunity cost, as landowners may find maintaining grazing practices and livestock production on the CRP-based grassland type practices a much higher value use and more beneficial for other reasons too.

Maintaining CRP grassland-type practices may increase wildfire risks. Landowners and producers may decide not to convert land to another use due to wildfire risk and maintain their CRP practices due to a perception that they are unable to manage or mitigate these risks (Bergtold et al., 2024). Land managers, though, need to consider wildfire risks and should manage these lands to reduce fuel loads and dry materials by implementing practices such as rotational grazing and prescribed burning (Anderson and Stubbendieck 2006; Steiner et al. 2020; Vandever et al. 2023).

According to the literature, CRP persistence is higher when the surrounding land is grassland. Based on the literature, the percentage of area used for crop production and under development around a parcel are two additional factors that may influence persistence (Barnes and Dayer 2021; Berger et al. 2020; Sullins et al. 2021). We also include the percentage of open water as a factor. We find that CRP persistence is influenced by the immediate surrounding land use, i.e. a 50m buffer around the expired CRP land. If crops border them, CRP persistence decreases, but it increases if surrounded by grassland or open water. However, when we look at a 1000m buffer surrounding land instead, the only significant land use that affects CRP persistence is grassland, which had a positive effect on CRP persistence. This is because with a larger surrounding consisting of grassland, it may be that conversion costs in these areas are much greater than in others, or the benefits in retaining CRP-based practice exceed other land management practice or it may be simply to retain conservation benefits, such as wildlife, and in some cases, uncertainty of future crop returns discourages the switch to cropland. Earlier studies have seen that expired CRP lands that are very close to farm land that belongs to the same landowner tend to be reversed to crop production, and a 1000m buffer may be capturing different landowners, making the results less significant (Barnes and Dayer 2021; Sullins et al. 2021).

As for environmental factors, all had a significant effect on CRP persistence except for long-term drought conditions. An increase in precipitation decreased CRP persistence, while an increase in temperature increased CRP persistence, which was also been observed by Sullins et al. (2021). In the dataset, we did not have any expired CRP parcels that had experienced severe drought, with most observations experiencing mid-range drought (82%), which was near-normal conditions. We measured drought using a long-term drought index. We speculate that because most observations were classified as mid-range drought, and the remaining 18% were in

moderately moist conditions, very moist, and extremely moist conditions. In order to see the impact of drought, we grouped observations based on the four categories. As we move from mid-range drought to extremely moist conditions, the probability of retaining land under CRP based practice decreases. However, when we used a short-term measure of drought, we see that CRP persistence decreases with an increase in drought. CRP reversal during short-term drought events is a way of coping with reduced crop yields. By clearing CRP fields, producers may increase their revenues by increasing planted area for a crop, increasing needed returns from crop production (Friedman 2023). In previous studies, most expired CRP wetlands had been reverted to crop production, and drought-prone areas were more likely to enroll in conservation programs (Morefield et al. 2016; Wallander et al. 2013; Sullins et al. 2021).

Despite land size not significantly influencing CRP re-enrollment (Caldas et al. 2016), it reduced CRP persistence after contract expiration (Sullins et al. 2021). In our study, we also observed that larger parcels were less likely to retain CRP-based practices. We did not observe any significant effect from soil type, land capability classification, wind erodibility index, or the Kw factor. Although other studies observed a negative effect on CRP persistence for parcels that were erodible, it was measured in terms of tillage risk, and this may explain the difference in results (Sullins et al. 2021). A significant amount of CRP enrollments are to enroll highly erodible land and environmentally sensitive land that is rehabilitated to grass, trees, or wildlife cover. We know that soil type, land capability classification, and erosion capability may be stable under a given land use over a short time period and irrespective of the physical parcel classification, the conservation practice introduced through CRP improves the quality of land. This may explain the insignificant results. Also, the effect of changes in soil and climate over time on land use decisions tends to be relatively small (Roberts and Lubowski 2007).

We then studied the effect of financial and economic factors on CRP persistence and found that they had a significant impact on CRP persistence. We computed a crop price index based on the four major crops in Kansas, which were corn, wheat, sorghum, and soybeans, and these were the four major crops that CRP land was converted to in Kansas. An increase in the crop price index decreased CRP persistence, and similar findings were also observed in other studies (Caldas et al. 2016; Hendricks and Er 2018; Atkinson et al. 2011; Sullins et al. 2021; Stubbs 2014; Bigelow et al. 2020). That is, as crops become more profitable to produce, CRP persistence decreases. We also found that an increase in population decreased CRP persistence as well. If CRP rental rates increase relative to land rental rates (land valuation), it is more likely that the expired CRP land will retain the CRP-based practice. In the past, lower CRP rental rates relative to land rental rates have discouraged CRP re-enrollment (Stubbs 2014; Roberts and Lubowski 2007).

6. Conclusion and Policy and Outreach Recommendations

CRP is the largest conservation program in the U.S. in which to enroll private agricultural lands (Barnes and Dayer 2021; Morefield et al. 2016; Roberts and Lubowski 2007; Bigelow et al. 2020). CRP enrollment was at its highest in 2007 and has been declining since 2012, reducing the conservation and environmental benefits from CRP in the long term (Bigelow et al. 2020). The situation is further challenged by the low rate of CRP persistence, which has ranged from as low as 15% to as high as 66 % on previously enrolled land (Sullins et al. 2021; Barnes et al. 2020; Roberts and Lubowski 2007). We define CRP persistence as the number of years in which grassland was the majority of the land use in an expired CRP contract parcel. Due to limited-term contracts under CRP, the conservation benefits on CRP land are not guaranteed in the long term. The long-term environmental benefits from CRP depend on how the CRP land is used after contract expiration. Recently, CRP land has been perceived as a fire hazard by producers and

landowners in the Mountain, Pacific, and Southern Plain regions of the U.S. (Allen and Vandever 2003; Bergtold et al. 2024). However, little is known about the effects of environmental and wildfire factors on landowners' decisions to revert expired CRP to cropland or other uses (Vandever et al. 2023). Specifically, we examine the influence of wildfires, drought, and surrounding land use on CRP persistence. To study this, we build a unique geodatabase at the CRP parcel level and use a Mixed Effects Weibull accelerated failure time model (AFTM) to assess the influence of environmental factors and surrounding land use on CRP persistence.

The mean CRP persistence for a CRP-based grassland or similar practices is 3.3 years, with most CRP reversals occurring within the first two years after contract expiration. However, as time progresses, CRP-based practices tend to persist. We found that environmental factors and surrounding land use play a significant role in shaping landowner decisions on whether to retain CRP-based practices on expired CRP land. For any expired CRP parcel, if the surrounding land was burned by a megafire, it was more likely for that parcel to persist in CRP-based practice, which was highly significant, contrary to initial expectations. This does not imply that megafire increased CRP persistence; on the other hand, it points to an indirect effect from wildfire risk on surrounding lands on CRP management. In addition, as the distance to a megafire increase, the probability of retaining CRP-based practice decreases, further enhancing the effect of megafire and wildfire risk on CRP persistence. One of the robustness checks conducted further examined this by incorporating an interaction of megafire damage within a 1000m buffer of the expired CRP parcel and the percentage of grassland within that same 1000m buffer. The estimated sign on that coefficient was positive and was highly significant. This result confirmed that these expired CRP parcels with higher CRP persistence due to the influence of megafire events on surrounding lands predominantly surrounded by grassland (i.e. 73% of the surrounding land was grassland on

average). While this result may seem contrary at first, the needed time for recovery from wildfire events and the potential for greater returns to grazing and forage production in such landscapes may drive such decisions. Given the likelihood of CRP persistence in these landscapes and greater wildfire risk due to higher fuel loads, wildfire mitigation practices, such as rotational grazing and prescribed burning, may need to be considered, especially on CRP land. In CRP active contracts, the contracts should be flexible and allow grazing and other fire management practices.

Based on our study, wetter conditions may reduce the conservation benefits that CRP provides in the longer term due to the potential for land cover conversion. Furthermore, expired CRP parcels predominantly surrounded by cropland had much lower rates of CRP persistence. Conversion to other land uses often occurred within two years after contract expiration. In order to ensure CRP's long-term success, there is a need for outreach and policy efforts to educate producers on the benefits of conservation and the opportunity costs and trade-offs of converting expired CRP land to crop production. In addition, to retain CRP-based practices on expired CRP parcels, the programmatic, policy, and outreach efforts should educate landowners and producers about the benefits of CRP-based practices (Thapa et al. 2024). Studies have shown that farmers and landowners can monetise their expired CRP parcels due to their recreational, environmental and aesthetic value from recreational activities such as hunting, fishing, bird watching, camping, wildlife watching, among others (Elmore et al. 2023; Blocksom et al. 2008; Southwick Associates and D. J. Case & Associates 2008). In addition, policy changes that improve the likelihood of reenrollment in CRP can be investigated if longer-term benefits of CRP on vulnerable lands are a policy goal. Current CRP parcels at risk of being converted if not enrolled include those in regions with higher rainfall, that are larger in size, are less connected to other CRP lands, are in dominant crop production regions, and/or are closer to areas of urban development. To make CRP re-

enrollment more likely, incentive payment levels under the program need to consider land rental rates, returns to crop production, and the growth in population.

We find that expired CRP parcels are less likely to be enrolled back into CRP if more time has passed, which may be due to enrollment lags and the auction-type system. In such cases, education campaigns should be carried out to encourage landowners to retain CRP-based practices after contract expiration and supplemented with detailed guidelines on how to care for expired CRP lands. This is important if landowners and producers plan to re-enroll their land into the CRP. In addition, the longer you can get a landowner to keep the CRP-based practice after expiration, the more likely it will persist. Education campaigns can also be carried out during periods of low enrollment. The messaging should be frequent, intentional, and motivational and should capture the percentage of parcels that still persist in CRP-based practice after contract expiration (Mouser et al. 2026; Race and Curtis 2013; Kuhfuss et al. 2016). All these interventions should be carried out within the first two years of contract expiration since the probability of reversal of CRP practice to other land uses is the highest during this time period. Alternatively, the government could consider longer CRP contracts to extend benefits from the program

A limitation of this study is that the dataset does not distinguish between normal grassland, pasture, or CRP parcels. Future research should include the Normalised Difference Vegetation Index (NDVI) or a similar measure to capture biomass changes or productivity, to further refine the analyses and provide a differentiated measure of grassland management. CRP persistence varies across landscapes, and we speculate that so will be the effect of environmental factors on CRP persistence (Sullins et al. 2021). This study was only done in Kansas, but further research is needed to determine if the effects of environmental factors on how CRP persistence varies other

ecoregions and landscapes. There is also a need to include landowners' household characteristics and landowners' perception, attitudes, values, norms, and beliefs towards environmental conservation, as these factors play a significant role in land use decisions (Caldas et al. 2016; Barnes and Dayer 2021; Chaudhary et al. 2026; Barnes et al. 2023; Atkinson et al. 2011). The understanding of the intersection of biophysical and social factors is important in maximizing the environmental benefits of conservation (Barnes and Dayer 2021). By also interviewing landowners, we can be able to determine if the CRP parcels that are retained in grasslands are enrolled in other land conservation programs, are being managed, and what activities are carried out, such as hunting, grazing, haying, etc.

Chapter 2 - Households' Willingness to Pay (WTP) to Avoid Power Outages from Catastrophic and Extreme Weather Events Along Frequency and Duration Dimensions

1. Introduction

Severe weather events and natural disasters have increased in frequency and severity in the past few decades due to climate change. Researchers anticipate that this upward trend in severe weather and natural disasters will continue to increase in the future (Titko et al. 2021; Robinson 2021; Zanocco et al. 2022; Committee on Extreme Weather Events and Climate Change Attribution et al. 2016; Fazeli et al. 2024; Smith and Katz 2013). The top four severe weather events and natural disasters that caused the most power outages were hurricanes, heavy winds, thunderstorms, and winter storms (Ali et al. 2022). Power outages from such events are expected to become more frequent and longer in duration (Executive Office of the President 2013; Zanocco et al. 2022; Baik et al. 2020; Macmillan et al. 2023; Brusentsev and Vroman 2017; Kenward and Raja 2014; Ali et al. 2022). Major power outages were ten times more likely in the 2000s compared to the late 1900s (Kenward and Raja 2014). Kenward and Raja (2014) found that 80% of large-scale power outages were caused by severe weather between 2003 and 2012, while Sayanti Mukherjee, Nateghi and Hastak (2018) found that 53% of major power outages were caused by severe weather and climate events between 2000 and 2016.

Resilience in power grids ensures critical electrical services are available during prolonged power outages due to severe weather events and natural disasters (Hotaling et al. 2021; Baik et al. 2018; Macmillan et al. 2023). It is 10 to 40 times more expensive for an individual to invest in alternative power sources themselves compared to collective options, such as alternative power

services from utility companies or community power investments (Bohman et al. 2022). The U.S. has an ageing electrical grid and power infrastructure that is more than 100 years old, making the country especially vulnerable to power outages caused by severe weather (Executive Office of the President 2013), which result from the destruction of large transmission lines or substations, more rarely occurring on smaller household distribution networks (Kenward and Raja 2014). This study examines households' willingness to invest in energy resilience at larger scales to reduce impacts of power outages from severe weather and natural disasters.

Resilience is achieved when there is a small supply of electric services to homes and communities during outages to sustain critical electrical-dependent services (Baik et al. 2020). These critical community electrical dependent services include medical and health services, water provision, sewage treatment, police and fire department services, and traffic lights, while for homes it's the ability to use needed medical equipment, power a refrigerator or freezer, and provide lights, as well as provide needed heat and air conditioning (Baik et al. 2020). The impact of power outages varies across the population. Vulnerable populations are often those households with children, who rely on electricity-dependent medical devices, lower-income, racial minorities, the elderly, and those in rural areas (Andresen et al. 2023; Kuang et al. 2024; Brown and Muehlenbachs 2024). These groups may be much more susceptible to power outages with an aging grid, less hardened, and with little diversification in the energy portfolio. However, types of investments in the electric grid and power systems that can increase resilience (e.g. electrical grid hardening, islanding, solar micro grids) are community dependent, and efficacy during severe weather and natural disasters will differ (Macmillan et al. 2023).

Grid resilience involves electric grid hardening, advanced capabilities, and recovery/reconstitution. (Executive Office of the President 2013). To build grid resilience and adopt

different resilience technologies, we must understand households' willingness to pay for such technologies in the case of an outage. Energy diversification in the U.S has increased, stabilizing energy production, and more states are using renewable sources of energy such as wind, solar, hydro, geothermal, and/or industrial waste (T. Y. Wu and Rai 2017; Odeh and Watts 2019). In order to determine if it's profitable to make investments to improve the reliability of power services, the cost of investment should not exceed the value of economic losses experienced by customers (M. J. Sullivan et al. 2009) or how much customers are willing to pay (WTP) to avoid unplanned power outages (Pacific Gas & Electric Company 2012). The investments can be in existing infrastructure or in adopting new energy sources. In the literature, this has often been done by examining households' willingness-to-pay to avoid an outage versus examining specific technologies, but much of this is in the context of regular power outages and not necessarily due to outages as a result of severe weather or natural disasters. There is a need to better prepare for severe weather events and natural disasters to reduce risk to people, infrastructure, and the economy, which requires an understanding of the impacts of power outages at different scales and contexts under such events (Kenward and Raja 2014).

Research on power outages has predominantly focused on welfare effects of power outages by measuring how much households are willing to pay (WTP) to avoid power outages with various characteristics for a general power outage (Carlsson and Martinsson 2007; Baik et al. 2020, 2018; Abdullah and Mariel 2010; Ozbaflı and Jenkins 2016; Pepermans 2011; Hensher et al. 2014; Amador et al. 2013; J. J. Cohen et al. 2016; Morrissey et al. 2018; Sagebiel and Rommel 2014; Chowdhury et al. 2004; Meles et al. 2021; Zemo et al. 2019; Niroomand and Jenkins 2020; Wen et al. 2022; Breit et al. 2016), while others have focused on the valuation of reliable electricity services to a community (Hotaling et al. 2021; Baik et al. 2020). Other studies have focused on

what factors determine the economic loss of power outages (Shuai et al. 2018; Küfeoğlu and Lehtonen 2015b; De Nooij et al. 2007) or have measured the economic cost of power outages with various characteristics (Campbell 2012; M. Sullivan et al. 2015; Lawton et al. 2003; M. J. Sullivan et al. 1996; Kristina Hamachi LaCommare et al. 2018). Many studies estimate the marginal or overall WTP to avoid power outages of various durations in the U.S. To the authors' knowledge, there exist no studies that specifically examine WTP to avoid a power outage that combines both frequency and duration in the context of severe weather events and natural disasters that often result in longer power outages and more severe conditions. In addition, much of this literature does not necessarily connect across population segments based on Metropolitan Statistical Areas (MSAs) and Non-Metropolitan Statistical Areas (N-MSAs) to assess differential impacts from power outages. The comparison is on household characteristics, such as estimating WTP values across households with and without backup services and the influence of past experience with a power outage on WTP values (Vallejo et al. 2022; Gorman 2022). Rural areas are likely much more susceptible to longer outages and impacts compared to urban areas (Call 2010; Gros et al. 2012). In Puerto Rico and Connecticut, longer-duration outages after Hurricane Maria happen more in rural municipalities compared to urban municipalities (Rouhana et al. 2025; Román et al. 2019; Sotolongo et al. 2021).

The purpose of this study is to estimate how much households are willing to pay (WTP) to avoid power outages that vary both in frequency and duration across states in the Great Plains of the U.S. as a result of severe weather events or natural disasters. A secondary objective is to assess differences in WTP across different population segments based on MSAs and N-MSAs. The WTP estimates provide a measure of what is known as the value of lost load (VoLL) for households

from an engineering perspective¹⁰. The WTP value is an indirect estimate of the monetary benefits of reliability improvements to the electricity grid. The WTP or VoLL can also be interpreted as the value of the indirect impact from power outages on households (European Commission. Joint Research Centre. 2018). Using primary survey data from a unique two-stage choice experiment, we determine if the duration and frequency of power outages influence WTP and at what level of duration and frequency the payment declines or if the households become disinterested in services that ensure resilient electrical services (i.e. reductions in the likelihood of power outages). We develop a conceptual framework and experimental approach to examine whether households are willing to pay to avoid a power outage that varies by duration (H1a), frequency (H1b), and the interaction between frequency and duration (H1c).

The unique two-stage choice experiment was based on Baarsma and Hop (2009). However, we estimated how much households are WTP to avoid power outages that vary in attribute levels as a result of a severe weather event or natural disaster. For each choice task, we adopted a conjoint analysis approach to estimate households' sub-utility derived from avoiding a power outage composed of different attributes. The first stage was the duration power outage task and captured the sub-utility of a household to avoid a single outage that varies by duration, season, time of day, time of week, and price. The second stage was the frequency power outage task, which measured the sub-utility of a household to avoid a set frequency of power outages over a given duration. We used random parameter linear regression models (RPLM) to estimate the duration and frequency sub-utility functions. The coefficients from two RPLMs in the two-stage choice experiment are used to estimate WTP values for various frequency and duration levels. To examine

¹⁰VoLL represents how much society is WTP to avoid power outage (Gorman 2022).

differences in WTP across population segments based on MSAs and N-MSAs, we estimated two separate RPLMs and used the coefficients to derive WTP values for various frequency and duration levels for these areas.

We find that the acceptable duration of outage varies across households, and on average, WTP values increase at a decreasing rate as the duration or frequency of outage increases. However, on average, WTP per hour is highest at a duration of 8 hours and declines afterwards. When accounting for both frequency and duration of outage, WTP values are much higher only if both the duration and frequency of outage are above an acceptable level or threshold that is unique and varies across households. If either the frequency or duration of the outage is within a household's acceptable level, the WTP is either zero or significantly lower. Comparing the results across population segments, we find that the mean acceptable duration of power outage did not vary significantly across MSAs and N-MSAs households, but MSA households were always WTP higher for backup services and the differences increase as the duration of the outage increases and eventually declines. The positive WTP values show that households are interested in alternative sources of power during severe weather outages and, therefore, a market exists for backup services.

This study contributes to the literature by estimating the acceptable duration of outage across households. It also provides novel estimates of WTP values to avoid severe weather power outages that vary by frequency, duration, and both frequency and duration at the household level and across different population segments (MSAs and N-MSAs). The WTP estimates provide VoLL, which can be used to compute the economic benefits of reducing extreme weather power outages that are crucial in determining pricing and investment decisions by power and utility companies or policy changes by the government (European Commission. Joint Research Centre.

2018; M. J. Sullivan et al. 2009; Gorman 2022). The government can determine if there is a need for policy changes or financial incentives to promote investments in alternative power sources to prevent power outages during severe weather events. Estimates can be used to assess levels for energy pricing and subsidies that improve social welfare and help households achieve energy resilience. As for households, they can use this information to determine if a market exists within their community for alternative sources of power that can enhance resilience during extreme weather events, and if they can take collective action to spread the cost of investment and maintenance to cushion themselves from extreme weather power outages. All these actions aim to improve household disaster energy resilience.

2. Background

Power outages have financial, infrastructural, and societal impacts (Macmillan et al. 2023; Ali et al. 2022). Using a bottom-up approach, Lacomme and Eto (2006) estimated that the national estimated cost of power outages in the U.S is about 79 billion annually, of which \$1.5 billion represents the cost to households. A more recent study estimates the annual national cost of power outages to be \$44 billion and \$1 billion for households (Kristina Hamachi LaCommare et al. 2018). These losses come from lost output and wages, spoiled inventory, delayed production, inconvenience, health costs, lost time, and direct damage to grid infrastructure (Executive Office of the President 2013; Ali et al. 2022). Specific economic costs and losses due to power outages depend on the geographic region, interruption frequency, interruption duration, season, user types, blackout time, and notification of power outage (Shuai et al. 2018; Campbell 2012; Küfeoğlu and Lehtonen 2015b; M. Sullivan et al. 2018; Do et al. 2023). While a one hour outage can significantly affect commerce, an 8-hour outage will begin to have significant adverse effects for health care and other important critical services (Do et al. 2023). These costs and damages are exacerbated by

extreme weather events and natural disasters. Costs and damage associated with such events have been increasing since 1980. Estimates were \$ 182 billion in 2024 and \$149.3 billion per year over the last 5 years (2020-2024) (Smith 2025). Power outages in the U.S caused by a severe weather event or natural disaster cost an estimated \$20 to \$55 billion annually (Campbell 2012; Kristina Hamachi LaCommare et al. 2018).

There are numerous studies on the valuation of the losses from power outages and how much households are willing to pay (WTP) to avoid these outages. The cost of a power system improvement is estimated using engineering cost analysis, while the expected economic benefit of the investment and the expected economic loss from power service interruptions are estimated using macroeconomic modeling, survey-based tools, or revealed preference consumer analysis (M. J. Sullivan et al. 2009; Gorman 2022). The economic cost of an outage is required for policy making to reduce the risk of power outages to customers.

Previous studies have documented the economic cost or loss from a power outage (the VoLL) across time for households (Layton and Moeltner 2005). In 1992, the average marginal cost for an hour outage on a summer afternoon for a household was valued at \$5.39 and ranged between \$0 and \$64 (M. J. Sullivan et al. 1996). The average marginal costs in 2008 were estimated at \$3.9 for an hour outage, \$7.8 for a 4-hour outage, and \$10.7 for an 8-hour outage (M. J. Sullivan et al. 2009). A study in the San Francisco Bay area and the rest of the Pacific Gas and Electric Company territory in 2012 observed that the cost of power interruption increased with the duration of the outage, and it varied by locality (Pacific Gas & Electric Company 2012). The average household's cost of power interruption in the Bay Area was \$13.22 for an hour outage, \$19.59 for a 4-hour outage, \$26.63 for an 8-hour outage, and \$37.83 for a day outage (Pacific Gas & Electric

Company 2012). For the same outage duration in a non-bay area, the cost of an outage was lower. An hour outage costs \$10.71, \$14.89 for a 4-hour outage, \$19.79 for an 8-hour outage, and \$26.03 for a day outage (Pacific Gas & Electric Company 2012). All three studies use survey data and use a customer damage function to estimate costs.

Sullivan, Schellenberg and Blundell (2015) did a study in 2013 on the cost of power interruptions for households across the entire U.S using a customer damage function. The cost of interruption for households was higher for morning or night outages, followed by afternoon and evening outages. The cost of interruption for summer outages was higher compared to any other season at the same time of day (M. Sullivan et al. 2015). The average cost of an outage was \$ 5.1 for a one-hour outage, \$9.5 for a 4-hour outage, and \$17.2 for an 8-hour outage (M. Sullivan et al. 2015). The weighted average cost per sustained power outage lasting 214 minutes (~3.6 hours) in the U.S. in 2015 for households based on primary survey data was estimated to be \$8.2 (Kristina Hamachi LaCommare et al. 2018).

WTP values for more reliable power services are important for undertaking resource planning and rate making for utility companies. There are various studies that have documented this in the U.S (Lawton et al. 2003; Hartman et al. 1991). A study by Hartman et al. (1991) using a contingent valuation survey on WTP for backup generator services found that WTP varied depending on the season, time of day, and duration of outage. For a one-hour outage, respondents were WTP \$2.95 to avoid an hour outage that occurred on a winter evening. For a 4-hour winter power outage, WTP was much higher, respondents were WTP \$4.78 to avoid an outage in the evening and \$2.99 in the morning, which is 1.6 times lower. The same was observed for a summer outage; WTP values increased with the duration of the outage. Respondents were WTP \$1.64 to

avoid one hour of outage in the afternoon and \$3.6 to avoid a 4-hour outage at the same time. A study by Layton and Moeltner (2005) conducted in the Fall of 1998 using a dichotomous choice contingent valuation survey examined how much households were WTP to avoid a power outage on a winter evening. They found that the WTP increases with the duration of the outage. Households were, on average, WTP \$13.45, \$25.17, \$34.49, and \$41.51 to avoid an hour, 4-hour, 8-hour, and 12-hour outage, respectively.

A study by Lawton et al. (2003) in the early 2000s using survey data collected from various sources found that WTP still varied based on outage duration. Households were WTP, on average, \$6.9 to avoid an hour outage, \$7.14 to avoid a 4-hour outage, and \$5.15 to avoid an 8-hour outage. The study covered the Southeast, most of the Western United States, and the Midwest, south and east of Chicago. A study in 2002 in the Midwestern US observed lower WTP to avoid power outages for some of the same outage durations. Households were WTP, on average, \$1.12 per month to avoid an hour outage, \$4.49 per month to avoid a 4-hour outage, and \$8.98 per month to avoid an 8-hour outage (Chowdhury et al., 2004). The estimates were derived from a WTP question on a mail survey. A study by Baik et al. (2020) using a stated preference approach in 2015 found that households were WTP, on average, \$43 per day to avoid a power outage. Another study in the Midwest in 2015 using a frequency bounded discrete choice method observed that households were WTP \$9 and \$11 on average for full-time and partial services, respectively, during a 24-hour outage when full information on what services were available (Baik et al. 2018). A long-duration study in New York State in 2018 using a choice experiment observed that respondents were WTP \$14 per month for full access to microgrid services as a back-up power source (Hotaling et al. 2021). A recent study by Stock et al. (2023) in 2020 using a stated preference approach estimated the WTP to avoid a power outage was on average \$15 to avoid an hour outage and \$252 for a 30-

day outage. They observed that WTP increased with an increase in outage duration. A study in California in late 2021 and early 2022, also using a stated preference approach, found that respondents were WTP \$78.44 per month on average to avoid a power outage (Gorman and Callaway 2024), while the average WTP for a 30-day power outage was \$252 in Los Angeles (Stock et al. 2023).

Our study builds on the literature by examining how much households are willing to pay to avoid a power outage resulting from severe weather events or natural disasters, rather than a general power outage or a specific severe weather event that has been extensively studied in the literature. We also compute the acceptable outage duration across households when WTP is \$0, or they are not willing to pay to avoid the power outage. We estimate WTP values to avoid severe weather power outages, which vary by frequency, duration, and both frequency and duration at the household level, and compare these WTP values across different population segments, which all contribute to the literature. We use the estimated mean WTP values to compute how long it will take in years to recover capital cost for an investment in alternative energy sources to prevent power outages based on various frequencies and durations of outages per year, building on existing literature.

3. Methods

3.1 Conceptual Framework

Our conceptual model is based on the framework proposed by Baarsma and Hop (2009), who were interested in households' WTP to avoid general power outages and enhance the reliability of the power grid in the Netherlands. In this study, we examine households' WTP value to avoid power outages resulting from severe weather events and natural disasters, reducing the likelihood of

outages during these types of events. We also examine the distribution of WTP at a household level across our study region, which differs from Baarsma and Hop (2009) who primarily focused on average WTP for their population.

We assume that household utility obtained for a back-up service to avoid a power outage from a severe weather event or natural disaster is a function of power outage duration (D) and frequency (F). Furthermore, we assume that the household utility function is weakly separable with respect to power outage duration and frequency. That is:

$$(1) \quad U = U(u(D), u(F))$$

Based on these assumptions, the utility function given by equation (1) can then be written as a function of sub-utility functions for D and F . The duration sub-utility function, $u(D)$, captures the conditional utility derived from avoiding a single outage that varies by duration, season, time of day, time of week, and cost (attributes). The sub-utility for frequency, $u(F)$, measures the conditional utility derived from avoiding a number of outages in a year that are similar in duration, season, time of day, and time of week but vary by cost¹¹. The sub-utility functions, assuming they are linear in the parameters, have the following functional forms:

$$(2) \quad U_0 = \alpha_i + \psi'_{ij}\beta_i$$

¹¹Our results support this approach empirically. When we estimated our frequency power outage model, duration was only significant as a linear term in the latent utility function. Interactions between duration and frequency were not statistically significant. This finding provides evidence that the duration and frequency may not directly interact, but only indirectly. The evidence is not definitive though and should be explored more in future research.

where i represents household, α_i is a household-specific constant, and ψ_{ij} is a vector of power outage attributes, and β_i is a vector of marginal sub-utilities. For the duration sub-utility function, equation (2) represents the utility obtained from a back-up service to avoid a single power outage of duration D from a severe weather event or natural disaster with ψ_{ij} vector representing duration, part of week, starting time of outage, season, and user fee. For the frequency sub-utility function, equation (2) represents the utility obtained from a back-up service to avoid a given size power outage of frequency F per year due to severe weather events and natural disasters with ψ_{ij} vector representing frequency of power outages and user fee. Following the literature, we assume that frequency and duration enter the utility function using a logarithmic specification to capture the nonlinear relationship between utility and duration and frequency of an outage (Baarsma and Hop 2009; Scarpa and Alberini 2005; Zemo et al. 2019; Kristina Hamachi LaCommare et al. 2018). The other attributes are assumed to have a linear relationship with the sub-utility for the duration and frequency of a power outage.

Following the framework by Baarsma and Hop (2009), now assume a household experiences two different power outages due to a severe weather event or natural disaster that have the same set of attributes, apart from duration and user fee. It should be emphasized that this is for a single power outage and does not directly incorporate frequency. That is, for power outage 1, the duration of the outage is D_1 and the cost or fee to avoid the outage using a back-up service is P_1^d , while the duration for power outage 2 is D_2 and the cost or fee to avoid the outage is P_2^d . D_2 can be written in terms of D_1 . That is, $D_2 = D_1 + \Delta$. Assume the difference in duration Δ of the two power outages is sufficiently small, such that the duration of sub-utilities is essentially equal. Based on equation (2), the duration sub-utility for the two different power outage events is given by:

$$(3) \quad U_0 = \alpha + \mathbf{X}'\boldsymbol{\beta} + \beta_D \ln D_1 + \beta_{PD}P_1^d, \text{ and}$$

$$(4) \quad U_0 = \alpha + \mathbf{X}'\boldsymbol{\beta} + \beta_D \ln D_2 + \beta_{PD}P_2^d = \alpha + \mathbf{X}'\boldsymbol{\beta} + \beta_D \ln(D_1 + \Delta) + \beta_{PD}P_2^d,$$

where $\mathbf{X}$ represents the season, time of day, and time of week. We have suppressed the individual subscripts here for convenience.

We hypothesize that the relationship between duration and user fee to be negative based on existing literature (Meles et al. 2021; Pepermans 2011; Zemo et al. 2019; Breit et al. 2016; Abdullah and Mariel 2010). Equations (3) and (4) can be rearranged to obtain the price P_2^d as a function of P_1^d , D_1 , the coefficient on duration (β_D), and the coefficient on the user fee (β_{PD}). That is:

$$(5) \quad \alpha + \mathbf{X}'\boldsymbol{\beta} + \beta_D \ln D_1 + \beta_{PD}P_1^d = \alpha + \mathbf{X}'\boldsymbol{\beta} + \beta_D \ln(D_1 + \Delta) + \beta_{PD}P_2^d$$

$$\beta_D \ln D_1 + \beta_{PD}P_1^d = \beta_D \ln(D_1 + \Delta) + \beta_{PD}P_2^d$$

$$\beta_{PD}P_2^d = \beta_D \ln D_1 + \beta_{PD}P_1^d - \beta_D \ln(D_1 + \Delta)$$

$$P_2^d = P_1^d - \frac{\beta_D}{\beta_{PD}} \ln \left(\frac{D_1 + \Delta}{D_1} \right)$$

When $\Delta > 0$ then $P_2^d > P_1^d$ and vice versa if $\Delta < 0$.

Let D_0 represent the duration of the power outage event that is acceptable to households in which their WTP is zero ($P_0^d = 0$) to avoid it. Based on Equation (5), the WTP to avoid a severe weather event or a natural disaster power outage of duration $D_n = D_0 + n\Delta$ can be calculated. D_n represents a power outage duration that households are WTP a user fee to avoid, where $D_n \in [D_0, \infty]$. The symbol Δ represents a fixed (marginal) time increment and n represents the number of time increments between D_0 and D_n . We assume here that $P_0^d = 0$ since households are not

WTP for a power outage that is of length D_0 or less. The user fee a household is WTP to avoid an outage of length D_n can be computed following equation (2) using a recursive equation as¹²:

$$\begin{aligned}
 (6) \quad P_n^d &= P_0^d - \frac{\beta_D}{\beta_{PD}} \sum_{i=1}^n \ln \left(\frac{D_{i-1} + \Delta}{D_{i-1}} \right) \\
 &= - \frac{\beta_D}{\beta_{PD}} \ln \left(\frac{D_0 + \Delta}{D_0} \right) - \frac{\beta_D}{\beta_{PD}} \ln \left(\frac{D_1 + \Delta}{D_1} \right) - \dots - \frac{\beta_D}{\beta_{PD}} \ln \left(\frac{D_{n-1} + \Delta}{D_{n-1}} \right) \\
 &= - \frac{\beta_D}{\beta_{PD}} \ln \left(\frac{D_0 + \Delta}{D_0} \right) \left(\frac{D_1 + \Delta}{D_1} \right) \dots \left(\frac{D_{n-1} + \Delta}{D_{n-1}} \right) \\
 &= - \frac{\beta_D}{\beta_{PD}} \ln \left(\frac{D_0 + n\Delta}{D_0} \right) = - \frac{\beta_D}{\beta_{PD}} \ln \left(\frac{D_n}{D_0} \right),
 \end{aligned}$$

which can be rewritten as:

$$(7) \quad P_n^d = \lambda_0 \ln(\lambda_1 D_n)$$

where $\lambda_0 = -\frac{\beta_D}{\beta_{PD}}$ and $\lambda_1 = D_0^{-1}$.

For the frequency sub-utility function, we again follow the framework based on Baarsma and Hop (2009) to obtain the utility level U_0 and the price level households are WTP to avoid a power outage due to severe weather or natural disasters with a given frequency. When only considering this sub-utility, duration must be set to a base power outage duration. Let this be φ . The base frequency sub-utility function follows equation (2). Now, assume a household experiences two types of power outages that are different based on the frequency with which they occur in a year. That is, for power outage Type 1, the frequency of outage per year is F_1 and for power outage Type 2, the frequency of outage is F_2 . We assume a household is WTP P_1^f and P_2^f

¹²The first equation writes the WTP equation as the sum of n time increments Δ . Using the product rule, the equations can be rearranged to obtain the second equation since the relationship between duration and user fee is negative. Some of the terms cancel out and we obtain the last equation.

in the form of a user fee to avoid power outages of duration φ and with frequency F_1 and F_2 , respectively. As with duration, F_2 can be written in terms of F_1 by letting $F_2 = F_1 + \Delta$. Again, the difference in frequency (Δ) of the two types of power outages is assumed to be sufficiently small such that the utilities of the two power outages are essentially equal. That is, the frequency sub-utility function for each type of power outage is given by:

$$(8) \quad U_0 = \alpha + \mathbf{X}'\boldsymbol{\beta} + \beta_F \ln F_1 + \beta_{PF} P_1^f, \text{ and}$$

$$(9) \quad U_0 = \alpha + \mathbf{X}'\boldsymbol{\beta} + \beta_F \ln F_2 + \beta_{PF} P_2^f = \alpha + \mathbf{X}'\boldsymbol{\beta} + \beta_F \ln(F_1 + \Delta) + \beta_{PF} P_2^f,$$

where $\mathbf{X}$ represents other attributes of the type of power outage. We have suppressed the individual subscript for convenience. Based on existing literature, we also assume the relationship between frequency and user fee to be negative (Meles et al. 2021; Pepermans 2011; Zemo et al. 2019; Abdullah and Mariel 2010).

We can arrange Equations (8) and (9) to obtain the following equation, given Δ is sufficiently small: -

$$(10) \quad \alpha + \mathbf{X}'\boldsymbol{\beta} + \beta_F \ln F_1 + \beta_{PF} P_1^f = \alpha + \mathbf{X}'\boldsymbol{\beta} + \beta_F \ln(F_1 + \Delta) + \beta_{PF} P_2^f$$

$$\beta_F \ln F_1 + \beta_{PF} P_1^f = \beta_F \ln(F_1 + \Delta) + \beta_{PF} P_2^f$$

$$\beta_{PF} P_2^f = \beta_F \ln F_1 + \beta_{PF} P_1^f - \beta_F \ln(F_1 + \Delta)$$

$$P_2^f = P_1^f - \frac{\beta_F}{\beta_{PF}} \ln \left(\frac{F_1 + \Delta}{F_1} \right)$$

When $\Delta > 0$, $P_2^f > P_1^f$ and vice versa when $\Delta < 0$. Generalizing, for any severe weather, power outage of frequency $F_n = F_0 + n\Delta$, the household is WTP P_n^f to avoid it, where n represents the number of equal marginal time increments Δ . We assume here that F_0 represents the least number

of power outages technically possible caused by severe weather events. We chose to set this at 0.05 (1 severe weather power outage every 20 years). P_0^f is the maximum user fee a household is WTP to avoid a severe weather power outage with the least frequency (F_0) and it is assumed $F_n \gg F_0$. Again, Δ is assumed to be sufficiently small. We follow the same procedure as for the duration sub-utility model to obtain a recursive equation and generalize equation (10) to obtain a representation for P_n^f for the frequency of outage.

$$(11) \quad P_n^f = P_0^f - \frac{\beta_F}{\beta_{PF}} \sum_{i=1}^n \ln\left(\frac{F_{i-1} + \Delta}{F_{i-1}}\right) = P_0^f - \frac{\beta_F}{\beta_{PF}} \ln\left(\frac{F_0 + n\Delta}{F_0}\right) = P_0^f - \frac{\beta_F}{\beta_{PF}} \ln\left(\frac{F_n}{F_0}\right),$$

which is equivalent to:

$$(12) \quad P_n^f \approx \mu_0 \ln(\mu_1[1 + \mu_2 F_n])$$

where $\mu_0 = -\frac{\beta_F}{\beta_{PF}}$, $\mu_1 = \exp\left(\frac{P_0^f}{\mu_0}\right)$, and $\mu_2 = F_0^{-1}$. Plugging in the values gives you an estimate of $P_n^f = P_0^f - \frac{\beta_F}{\beta_{PF}} \ln\left(1 + \frac{F_n}{F_0}\right)$. By adding a value of 1 in the equation, the price is no longer undefined for a frequency of zero¹³. We have also suppressed the individual subscript i for convenience.

There exists a frequency of power outages (F_M) in which households are not WTP anything ($P_m^f = 0$). We assume this occurs at the frequency F_0 or 0.05 (once every 20 years). This assumption implies that $F_M = F_0$ and $P_m^f = P_0^f = 0$. Thus, F_0 represents the maximum frequency for a given power outage duration due to severe weather events or natural disasters that is

¹³We use $\ln(1 + F_n)$ instead of $\ln(F_n)$ to ensure pricing is defined at frequency level of zero (Stock et al. 2023).

Although we observe a small difference in mean pricing equations at a frequency lower than $F_n=0.5$ (1 outage every other year), in higher frequency the mean pricing was almost similar.

acceptable for a household where WTP to avoid that frequency of outage is zero. For power outages with a frequency equal to or below F_0 , $P_n^f = 0$ and for those power outages with frequency above F_0 , $P_n^f > 0$. From these assumptions, for any outage frequency of 1 outage every 20 years (0.05) and below, $P_n^f = 0$ because $F_0 \leq 0.05$ and $P_n^f > 0$ if $F_0 > 0.05$.

At a given frequency for a set duration of outage, there exists a WTP for household i such that $P_n^d = P_n^f = P_n$. That is, Equations (7) and (12) can be set equal to each other. This must be determined empirically, which is captured in the designed choice experiment developed later in the paper. We chose a base power outage duration of φ for this purpose. With $D_0 = \frac{1}{\lambda_1}$:

$$(13) \quad \lambda_0 \ln(\lambda_1 D_n) = \mu_0 \ln(\mu_1 [1 + \mu_2 F_n])$$

$$\lambda_1 D_n = \exp\left(\frac{\mu_0}{\lambda_0}\right) \mu_1 [1 + \mu_2 F_n]$$

$$\frac{1}{\lambda_1} = \frac{D_n}{\exp\left(\frac{\mu_0}{\lambda_0}\right) \mu_1 [1 + \mu_2 F_n]}$$

$$D_0 = D_n (\mu_1 [1 + \mu_2 F_n])^{-(\lambda_0^{-1} \mu_0)}$$

$$D_0 = \varphi (\mu_1 [1 + \mu_2])^{-(\lambda_0^{-1} \mu_0)}$$

We assume that for a household, D_0 , which is the duration of a severe weather power outage that is acceptable to households in which their WTP is zero, is the same for all frequency levels with this set duration ¹⁴. The assumption enables us to estimate the valuation of different outages that vary in duration at various frequency levels. We capture the interaction effect between

¹⁴By assuming D_0 varies across frequency levels, we will need to estimate a separate, theoretically consistent framework for each frequency level, which is not empirically feasible.

duration and frequency by first assuming that λ_o is a function of F_n in Equation (7). Recall, λ_o is the negative of the ratio of the marginal sub-utility of a given power outage duration relative to the marginal sub-utility of the user fee a respondent would need to pay to avoid that outage. This assumption allows for the sub-utility functions to then be connected, such that duration sub-utility is indirectly influenced by frequency, which must occur following the weak separability assumption of an individual's overall utility function, considering duration and frequency of power outages. We can determine $\lambda_o(F_n)$ here by setting $D_n = \varphi$ as we did above and again by equating equation (7) to equation (12), giving:

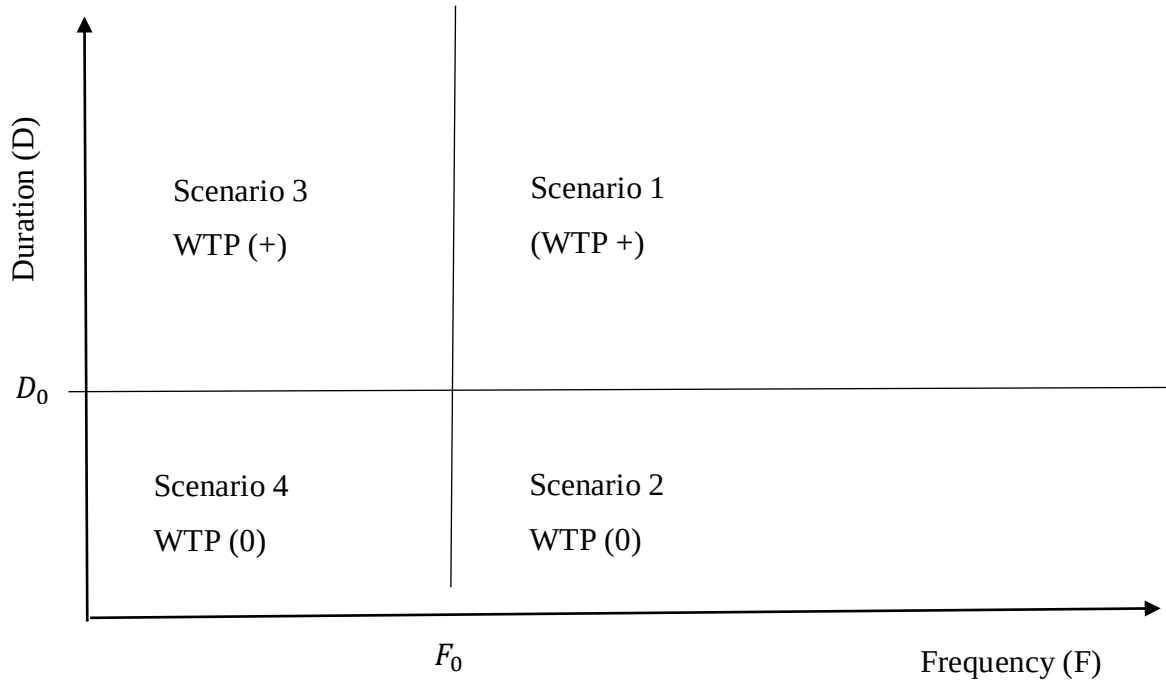
$$(14) \quad \lambda_o(F_n) \ln(\lambda_1 D_n) = \mu_o \ln(\mu_1 [1 + \mu_2 F_n])$$

$$\lambda_o(F_n) = \frac{\mu_o \ln(\mu_1 [1 + \mu_2 F_n])}{\ln(\lambda_1 D_n)} = \frac{\mu_o \ln(\mu_1 [1 + \mu_2 F_n])}{\ln\left(\frac{\varphi}{\varphi (\mu_1 [1 + \mu_2])^{-(\lambda_o^{-1} \mu_o)}}\right)} = \frac{\lambda_o \ln(\mu_1 [1 + \mu_2 F_n])}{\ln(\mu_1 [1 + \mu_2])}$$

We can use Equation 14 to obtain the WTP values at various possible combinations of frequency and duration. We know that at the duration of D_0 and below, a household's WTP to avoid a severe weather power outage of duration D_0 is zero, no matter the frequency of outages at this duration. Households are only interested in power services when power outage durations are greater than D_0 . For frequency, we know that households are not WTP for any frequency of severe weather outages less than F_0 .

There are four possible scenarios to consider when examining the interactions between power outage duration and frequency. The WTP values of the four possible scenarios are illustrated in Figure 2.1 and outlined below. We dropped the n subscript on F_n for simplification purposes.

Figure 2.1. Four Possible Scenarios of Frequency and Duration Combination



Scenario 1: The user fee households are WTP to avoid a power outage due to severe weather or a natural disaster of duration $D > D_0$ for a given outage frequency $F > F_0$ is positive and is given by:

$$(15) \quad WTP(D|F > F_0) = \lambda_o(F) \ln(\lambda_1 D) = \lambda_o \frac{\ln(\mu_1[1 + \mu_2 F])}{\ln(\mu_1[1 + \mu_2])} \ln(\lambda_1 D).$$

$WTP(D|F > F_0)$ is positive because households are WTP for any severe weather power outage that is greater than D_0 and a frequency greater than F_0 , which is above both the base acceptable levels for duration and frequency of outages, households are willing to pay for. It is expected that in this situation, households will invest in alternative power sources or change their residence if a backup power service is not available.

Scenario 2: The user fee households are WTP to avoid a power outage due to severe weather or a natural disaster of duration $D \leq D_0$ for a given outage frequency $F > F_0$ is equal to zero. In equation (15), since the value of $\ln(\lambda_1 D)$ is negative, then $WTP(D|F > F_0)$ is negative. While negative values can be estimated and would capture household's preferences at various frequency levels when $D \leq D_0$, we do not expect power companies to compensate customers for using their services during a power outage. In addition, any severe weather power outage with a duration of D_0 or lower is assumed to be acceptable by households at any frequency for this duration, not making them interested in paying for a back-up service. Thus, $WTP(D|F > F_0) = 0$.

Scenario 3: The user fee households are WTP to a power outage due to severe weather or a natural disaster of duration $D > D_0$ for a given outage frequency $F \leq F_0$ is positive and not influenced by frequency. We know that any severe weather power outage with a duration higher than D_0 is unacceptable to households, and they are WTP to avoid it. However, households are not WTP anything for $F \leq F_0$. We can rewrite equation 15 to obtain how much households are WTP at various duration levels, which is equal to $\lambda_0 \log(\lambda_1 D)$. The value $\lambda_0 \log(\lambda_1 D)$ captures WTP to avoid a single event. To obtain WTP, we multiply $\lambda_0 \log(\lambda_1 D)$ by frequency (F) to capture the frequency of severe weather power outages¹⁵. The WTP becomes:

$$(16) \quad WTP(D|F \leq F_0) = F\lambda_0 \ln(\lambda_1 D)$$

Scenario 4: The user fee households are WTP for a power outage due to severe weather or a natural disaster of duration $D \leq D_0$ for a given outage frequency $F \leq F_0$ is zero. We know that for any

¹⁵ The equation is different from Baarsma and Hop (2009) paper because we excluded $(1-F_0)P_0$, this is because at all frequency below or equal to F_0 , $P_0 = 0$ and it collapses to zero.

severe weather power outage with a duration of D_0 or lower, WTP for the back-up service will be zero. In addition, households are not WTP for any frequency of severe weather power outage at F_0 and below.

3.2 Empirical Model

The empirical model builds upon the conceptual and empirical framework proposed by Baarsma and Hop (2009). For the empirical modelling framework, a random parameter linear regression model (RPLM) is adopted to capture household unobserved heterogeneity. The dependent variable in the model is the choice task rating by respondents from the discrete choice experiment. The rating marks estimate utility derived from a good composed of attribute levels (Baarsma and Hop 2009; Maddala, Phillips and Reed Johnson 2003; Poortinga et al. 2003; Green and Srinivasan 1990). This is based on their subjective willingness-to-pay to avoid a power outage of a given duration and/or frequency.

We estimate a RPLM following the methods described in Greene (2018) to empirically estimate the duration and frequency sub-utility functions given by Equation (2). We regressed the choice task rating on the attributes of the extreme weather power outage scenario denoted by ψ from the discrete choice experiments. We estimate a different model for both the duration and frequency sub-utility functions. Social or economic variables were not included in the initial model, because past literature has provided evidence that the ratio of the coefficients of duration and frequency to changes in monthly electric bills does not change with additional explanatory variables in the econometric model (Baarsma and Hop 2009). However, we did a robustness check by including a number of social and economic variables to check for this study, as that finding may be problem-dependent.

We assume a utility function linear in the parameters, but duration and frequency enter nonlinearly, which was based on functional forms and evidence from the literature. We further assumed that all random parameters in the linear regression models estimated follow a normal distribution. This distributional assumption allows the mean of the distribution and household parameter estimates to have a positive or negative sign that captures heterogeneity in preferences across households (Carlsson et al. 2003). We initially assume that the random parameters are uncorrelated, but then test this assumption, assuming the random parameters come from a multivariate normal distribution.

The RPLM adopted is specified as:

$$(17) \quad w_{ij} = \alpha_i + \boldsymbol{\psi}'_{ij}\boldsymbol{\beta}_i + \varepsilon_{ij}$$

where i represents household i , w_{ij} is the rating of choice task j for household i , α_i is the household-specific constant, $\boldsymbol{\psi}_{ij}$ is the vector of attributes from the discrete choice experiment (e.g. duration, part of week, starting time of outage, season, frequency and/or user fee), $\boldsymbol{\beta}_i$ is a vector of random parameters that follows a multivariate normal distribution with mean $\mathbf{b}$ and covariance matrix $\mathbf{H} = \boldsymbol{\Lambda}\boldsymbol{\Lambda}'$, and ε_{ij} is a mean zero IID error term. That is, we assume $\boldsymbol{\beta}_i = \mathbf{b} + \boldsymbol{\Lambda}\mathbf{u}_i$, where $\boldsymbol{\Lambda}$ is a diagonal covariance matrix with a standard deviation $(\sigma_1, \dots, \sigma_k)$ on the diagonal and $\mathbf{u}$ is a random vector such that $\mathbf{u} \sim N(\mathbf{0}, \mathbf{I})$, where $\mathbf{I}$ is an identity matrix.

In their framework, Baarsma and Hop (2009) transform the rating marks that represent the responses in the DCE. This transformation assumes that respondents attach the same mean rating for the average reliability of power supply in any given choice task. This method corrects for

unobserved heterogeneity, but only in the intercept, not for preferences of other choice attributes.

The transformation for rating mark used by Baarsma and Hop (2009) is:

$$(18) \quad \omega_{ij} = w_{ij} - \frac{1}{K} \sum_{j=1}^K w_{ij}$$

where i represents household i , w_{ij} is the rating of choice task j for household i , and K is the number of choice tasks answered by household i . We estimate the RPLM with the transformation given by equation (18) and assuming the coefficients on the attributes (i.e. marginal sub-utilities) in the model do not vary across respondents as a robustness check.

The WTP values for various frequency and duration levels are estimated using the coefficients from the estimated RPLM. To do this, we first estimate the duration sub-utility RPLM to obtain household coefficient estimates of the price (β_{pDi}) and duration (β_{Di}) parameters following Greene (2018). That is, we estimate the RPLM and the random parameter distributions for the price (β_{pDi}) and duration (β_{Di}) parameters. We treated duration and user fee as continuous variables and season, time of week, and time of day as categorical variables, which will be discussed later in the choice experiment. Duration enters the sub-utility nonlinearly as $\ln D$. We then follow methods in Greene (2018) to obtain household (or respondent) specific price (β_{pDi}) and duration (β_{Di}) parameters from the estimated distributions. These are used to then estimate household-specific WTP estimates by using the equations in the conceptual model. To estimate how much households are WTP to avoid power outages at various outage durations for a single outage, as in Equation (7), we need to be able to estimate $D_0 = \frac{1}{\lambda_1}$. We can obtain household-specific estimates for $\lambda_0 = -\frac{\beta_D}{\beta_{pD}}$ that is later used to compute D_0 .

The next step was to estimate the frequency sub-utility RPLM. We followed the same steps as for the duration sub-utility RPLM to obtain the household-specific parameters for price (β_{PFi}), frequency (β_{Fi}), and the constant term (α_i). Frequency and user fee were continuous variables, and the base category of duration was a categorical variable to control for the base duration effects. Frequency enters nonlinearly as $\ln(1 + F)$.

After estimating the frequency sub-utility RPLM, we then proceed to estimate how much households are WTP to avoid a severe weather power outage of frequency F_n following Equation (12). We estimate household-specific coefficients for $\mu_0 = -\frac{\beta_F}{\beta_{PF}}$ and $\mu_1 = \exp\left(\frac{P_0}{\mu_0}\right)$ by substituting the household-specific parameters for price (β_{PF}) and frequency (β_F) we obtained above and P_0 which is assumed to be zero (see the conceptual framework for details). This then provides us with a method based on the conceptual framework to determine how much households are WTP at various frequencies (F_n) of outages based on a given base category of duration.

Using the household-specific coefficient estimates above, household-specific parameter estimates of D_0 can be obtained following Equation (13) by plugging in the base duration of severe weather power outage for φ , μ_1 , μ_0 , λ_0 , and $\mu_2 = F_0^{-1}$. After computing D_0 , household-specific estimates of WTP to avoid a severe weather power outage with a given duration D_n using Equation (7) can be obtained by first estimating $\lambda_{1,i} = D_{0,i}^{-1}$ and plugging it into Equation (7) with the estimated values for $\lambda_{0,i}$, and D_n , providing household estimates of how much a household is WTP to avoid a severe weather power outage of duration D_n .

We can now consider estimation of how much households are WTP to avoid a power outage that varies by both frequency and duration. To do this, household-specific estimates are

obtained for $\lambda_o(F)$ using Equation (14). Recall, there are four possible combinations of frequency and duration, and we can use Equation 14 to obtain these WTP values (see the conceptual model section). For Scenario 1, we use household-specific estimates of $\lambda_o(F)$, λ_1 , and D in Equation (15) to obtain how much households are WTP to avoid a severe weather power outage of duration $D > D_0$ for a given outage frequency $F > F_0$. The WTP to avoid severe weather power outages of duration $D \leq D_0$ for a given outage frequency $F > F_0$ in Scenario 2 is assumed to always be zero. For Scenario 3, we estimate household WTP to avoid a severe weather power outage of duration $D > D_0$ for a given outage frequency $F \leq F_0$ by plugging in the household-specific estimates of λ_o and λ_1 , as well as the levels for F and D into Equation (16). The WTP to avoid a severe weather power outage of duration $D \leq D_0$ for a given outage frequency $F \leq F_0$ in Scenario 4 was again assumed to always be zero.

4. Data

4.1 Choice Experiment

A two-stage choice experiment was developed to estimate households' WTP to avoid power outages that vary in attribute levels due to extreme weather and natural disasters. The design is based on that proposed by Baarsma and Hop (2009). We ask respondents to rate their intention of paying for a backup service to avoid a power outage due to a severe weather event, based on different power outage attributes. We use this continuous response as a measure of the sub-utilities in the theoretical framework. The first stage of the experiment was a duration power outage task, and the second stage was a frequency power outage task due to severe weather. We used the two-stage choice experiment to limit the number of choice sets and ensure enough variability in the attributes, as well as better capture the marginal impact of duration and frequency and the

interaction between duration and frequency (Baarsma and Hop 2009). The duration power outage task, or the one-time power outage part of the experiment, was used to capture the WTP of a household to avoid a single outage that varies by duration, season, time of day, user fee, and time of week. The frequency power outage task or multiple power outages part of the experiment was used to capture the WTP of a household to avoid a set frequency of power outages at a given duration. A user fee was included in both experiments to enable estimation of WTP for each power outage attribute. The WTP values can provide marginal and overall valuation of indirect effects on households from power outages during extreme weather events and natural disasters, sometimes known as the value of lost load (European Commission. Joint Research Centre. 2018).

Reliability of power supply to households is often measured in terms of frequency of outages, duration of interruption, time of day, notification of interruption, and price (Hensher et al. 2014; Amador et al. 2013; Bhatia and Angelou 2015; Blass et al. 2010). The cost per outage is not constant and varies depending on the duration, frequency, season, day of the week, region, the type of customer, and time of day (Lawton et al. 2003; Carlsson and Martinsson 2007; C.-K. Woo and Pupp 1992; Ozbaflı and Jenkins 2016). In our study, we measured reliability by duration of outage, frequency of outage, season in which the outage occurs, user fee, and time of week and day. The choice of attributes for the study is based on previous literature and discussion with experts in the field (Ozbaflı and Jenkins 2016; Pepermans 2011; Hensher et al. 2014; Amador et al. 2013; Blass, Lach and Manski 2010; Morrissey et al. 2018; Cohen et al. 2016; Meles et al. 2021; Zemo et al. 2019; Breit et al. 2016; Carlsson et al. 2020). We chose not to include notification of interruption given the focus on severe weather and natural disasters. The choice task developed already takes the potential of an outage from the event into account. Tables 2.2 and Table 2.3

summarize the attributes and attribute levels used in the choice experiment for both the duration outage task and the frequency of outage task.

Duration is a critical component in determining the impact of an outage (De Nooij et al. 2007). The average estimated monthly power bill in the U.S. ranges between \$75 and \$203 and \$81 and \$128 based on our study region (Electricity Local 2023). In our study, we limit the user fee to a maximum of \$250, the high end of average monthly electric bills in the U.S. The duration levels we chose are based on prior literature and experienced power outages in our region (Carlsson et al. 2020; Meles et al. 2021; Küfeoğlu and Lehtonen 2015b, 2015a; Kim et al. 2020; Zemo et al. 2019; Wen et al. 2022; Scarpa and Alberini 2005; Pepermans 2011; Carlsson and Martinsson 2007; Carlsson et al. 2011; Abdullah and Mariel 2010; Baarsma and Hop 2009; Lawton et al. 2003). We selected 1 hour, 4 hours, and 8 hours to limit the levels in short-duration outages, as we were also interested in including longer-duration outages that may result from more severe weather events. Most power outages in the U.S. are less than 48 hours, with a few lasting for a longer period, e.g. more than a week. Thus, we limit the longest duration of outage to 5 days (Taimoor et al. 2020). We anticipated that including a longer duration would not be viable since households may relocate to escape the adverse effects of the outages that last longer than 5 days. We selected 3 days as a midpoint between having a 1-day and a 5-day outage.

The season, day of the week, and time of day influence which activities are interrupted. These activities are valued differently by households (De Nooij et al. 2007; Blass et al. 2010; J. J. Cohen et al. 2016). Households' WTP are likely higher during weekends and weeknights relative to weekdays (Carlsson and Martinsson 2007). A higher number of activities usually happen in the early morning prior to going to work and late afternoon/evening when people return home and

prior to going to bed (Casey et al. 2020). For example, an outage that happens at 8 p.m. can affect household leisure and labour activities, while an outage at 3 a.m. has less of an effect as most people are usually asleep (De Nooij et al. 2007). These are the reasons we include different time intervals for the time of day of an outage. These intervals represent the start time of the interval and include 6 a.m. – 10 a.m. (morning), 10 a.m. – 4 p.m. (afternoon), 4 pm to 10 pm (evening) and 10 pm to 6 am (night) in order to capture different variations of activities within households. Time of outage has often been used by various studies to estimate WTP to avoid power outages (Küfeoğlu and Lehtonen 2015a; Scarpa and Alberini 2005; Baarsma and Hop 2009; Lawton et al. 2003). Other temporal attributes include part of the week (Carlsson and Martinsson 2007; Baarsma and Hop 2009). We opted for the weekend and weekday to reduce the levels of this attribute in the experiment. Other studies have also included season as a level in their power outage experiments (Küfeoğlu and Lehtonen 2015b, 2015a; Pepermans 2011; Carlsson and Martinsson 2007; Baarsma and Hop 2009; Lawton et al. 2003). We selected summer and winter because most power outages in the U.S. tend to occur in late summer and mid-winter months (Casey et al. 2020; Do et al. 2025; Hines et al. 2009). In addition, there is a high demand for power during these times due to potentially extreme or higher heat and cold relative to the rest of the year (Michelfelder and Pilotte 2022).

The frequency of outages can be used to determine how much households may invest in or desire backup power options. Households are likely willing to pay more for an increase in the number of outages, but it is not well known if WTP increases at a decreasing or increasing rate as frequency increases. We explore this question in our study with the second stage of the choice experiment (Chowdhury et al. 2004). The frequency levels chosen for the second stage of the choice experiment were based on the reported occurrence of severe weather events and disasters

(Brusentsev and Vroman 2017; Casey et al. 2020; Woo et al. 2021; National Centers for Environmental Information (NCEI) 2020). Brusentsev and Vroman (2017) documented the frequency of major wildland fires, tornadoes, and hurricanes (tropical storms) between 1953 and 2013. The frequency of these events was on average between 1 and 3 per year, whereas between 2011 and 2017, there were 16 weather and climate disaster events, translating to roughly 2 events per year (National Centers for Environmental Information (NCEI) 2020). A study by Casey et al. (2020) showed the number of outages per state caused by severe weather events between 2000 and 2016. Based on our study region, it was 65 in Texas, 5 in Kansas, 17 in Oklahoma, and 3 in Nebraska, which was on average about 1 per year across these four states. However, in Colorado and Iowa, the primary cause of outages was electromagnetic events and intentional cyber-physical attacks, and the number of outages was 5 in each state for the period of 2000 to 2016.

For our choice experiment, each choice task utilized a conjoint analysis approach that captures stated preferences using rating marks to estimate an households' utility derived from a good composed of attribute levels (Baarsma and Hop 2009; Maddala et al. 2003; Poortinga et al. 2003; Green and Srinivasan 1990). We decided to present only a single choice option at a time to maintain incentive compatibility, which guided the experimental design. We also used a single-choice option because it tends to be more realistic, makes the experiment simple, and you can directly compute values for a single attribute (Weng et al. 2021; Rolfe and Bennett 2009). Apart from the design, it was made clear in the study that the choices were independent to maintain incentive compatibility.

The full factorial for the duration power outage task of the experiment had 576 different choice scenario combinations based on given attribute levels, see Table 2.1. To reduce this number

and identify the main effects, we developed an orthogonal fractional factorial design using the PROC OPTEX command in SAS to obtain 72 choice sets that were divided into 18 blocks consisting of 4 choice sets each. The D-optimality was 99.77 for the choice experiment design. For practical purposes and following the literature, we did not include interaction effects between attributes¹⁶. Each respondent was randomly assigned to one of 18 blocks of 4 choice questions for the duration power outage task.

Table 2.1. Duration Power Outage Task Attributes and Levels

Attributes	Duration Power Outage Task Attribute levels						
	Duration of Power Outage (Hrs.)	1 hour	4 hours	8 hours	24 hours (1 day)	72 hours (3 days)	120 hours (5 days)
	Season when the Outage Occurs	Winter	Summer (Base)				
	Part of the Week the Outage Occurs	Weekday	Weekend (Base)				
	Starting Time of the Outage	Morning at 6 a.m.	Afternoon at 10 a.m.	Evening at 4 p.m.	Night at 10 p.m. (Base)		
	User fee Charged	\$5	\$10	\$25	\$50	\$100	\$250

In order to connect the two experiments, we had to fix the time of day, time of week and season for the power outage frequency task. In addition, we also have to fix the duration, but we examined if results changed due to a change in the base duration by examining both an eight-hour outage (short duration outage) and a 24-hour outage (long-term outage) that occurred at 6 a.m. on a winter weekday following our conceptual framework. This is in contrast to the approach of Baarsma and Hop (2009). We wanted to explore how WTP for frequency would change when the

¹⁶ We also estimated a design with main effects and interactions using PROC OPTEX command in SAS. The optimal design had 288 choice sets and retaining the same 4 choice sets per respondent would require 72 versions of the questionnaire which was not practical for our experimental design.

power outage duration was a shorter duration versus a longer duration. For each scenario, we had two attributes: frequency and user fee charged. Table 2.2 provides the attributes and levels for the frequency outage task. Using PROC PLAN in SAS, we obtained the full factorial design that had 36 different choice combinations for each scenario based on attribute levels for the second stage. Thus, we used the full factorial, blocking it into 9 blocks consisting of 4 choice sets each. Respondents were randomly assigned to the 8 or 24-hour outage group and one of the 9 blocks in that group.

Table 2.2. Frequency Power Outage Task Attributes and Levels

Attributes	Frequency Power Outage Task Attribute levels						
	Number of Outages	2 per year (F=2)	4 per year (F=4)	1 per year (F=1)	1 every other year (F=0.5)	1 every 5 years (F=0.2)	1 every 10 years (F=0.1)
	User Fee Charged	\$5	\$10	\$25	\$50	\$100	\$250

In the survey, we presented a brief description of the outage conditions with attributes, as well as back-up service provision and fee (see Figure 2.2 and Figure 2.3 below). To reduce hypothetical bias we built in cheap talk, consequentiality, and cost uncertainty text following Vossler, Doyon and Rondeau (2012) and other sources (Niroomand and Jenkins 2020; Deutschmann et al. 2021; Carlsson et al. 2020). The participants in the study were asked to view each scenario as a real event they would face and be honest when answering the questions. They were also asked to make sure to take into consideration their actual place of residence, household income, and monthly electricity bills when answering the questions (cheap talk). As for consequentiality, they were told the information was important in understanding how households value backup power services and assist in improving the reliability of their local energy services. We built in the cost uncertainty by informing them that the exact fee for the type of backup service

was uncertain due to the unpredictability of severe weather and disasters, as well as advances in solar and energy technology.

Figure 2.2. Duration Power Outage Task (One-Time Power Outage)

Suppose there is a power outage in your area due to severe weather (e.g. ice storm, blizzard, high winds), disaster (e.g. tornado or flooding), or similar extreme event. Assume you now have the option of a backup service for your residence that can provide normal power during the outage. If you use the service, you will not experience the power outage, but you will be charged a fixed user fee for the service. The fee will be the same for everyone and is charged for each time you use the service.

The user fee will appear as an additional charge on your next monthly power bill if the service is used. If you do not use the service, you will experience the full outage from the event and your utility bill will not change. The exact fee for the type of backup service is uncertain, given the unpredictability of severe weather and disasters, and advances in solar and energy technology.

We will now ask you to consider a series of questions about a one-time power outage, followed by a separate set of questions concerning multiple power outages. You will be asked to consider 4 hypothetical situations for each case. We want you to rate each hypothetical situation based on your intention of paying for the backup service. The information collected will help us understand how you value these services and assist in improving the reliability of energy services provided to you.

Please view each situation presented as a real event you would face and be honest when answering the questions. Make sure to take into consideration your actual place of residence, households' income, and monthly electricity bills.

One Time Power Outage: Please consider 4 different hypothetical situations for a duration power outage due to severe weather or natural disaster. For each situation, we tell you (1) how long the outage will last; (2) when the outage occurs; (3) the start time for the outage; (4) the time of year the outage occurs; and (5) the user fee you would pay to access the backup service. Remember you pay the user fee for each event. Assume that there will be no direct notification of the power outage, but a warning of severe weather or potential disaster will be given.

For each situation, rate your intention of paying for the backup service on a scale of 1 to 9. A rating of 6 or higher indicates that you would lean towards paying for the backup service with a rating of 9 telling us you would definitely pay for the back-up service. A rating of 4 or lower indicates you would be less likely to pay for the backup service, with a 1 telling us you would definitely not pay for the backup services. A rating of 5 indicates you are unsure about paying for the backup services. You should rate each option as if each option was the only one presented. Please, note that it is possible to rate several situations with the same rating.

	Situation 1
Duration of the power outage (hours)	5 days (120 hours)
Part of the week the outage occurs	Weekend
Starting time of the outage	6 a.m.
Season when the outage occurs	Winter
User fee charged	\$100
Willingness to Pay for the Back-Up Service:	

☐ Definitely Not Pay
 ☐ Less Likely to Pay
 ☐ Unsure
 ☐ More Likely to Pay
 ☐ Definitely Pay

1 2 3 4 5 6 7 8 9

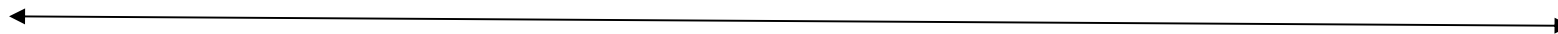


Figure 2.3. Frequency Power Outage Task (Multiple Power Outages)

Multiple Power Outages: Please consider 4 different situations where your power goes out during severe weather or a disaster event over a years' time. For each situation, we assume the power outages will take place on a **winter morning, on a weekday**. The outage **starts at 6:00 a.m. and lasts for 8 hours**. We want to know about your use of the back-up service based on (1) how often this type of power outage may occur during the winter (mid-November to mid-March) and (2) the user fee you would pay for the backup service. Remember you pay this fee for each event. Assume that there will be no direct notification of a power outage, but a warning of severe weather or potential disaster will be given.

For each situation, rate your intention of paying for the backup service on a scale of 1 to 9. A rating of 6 or higher indicates that you would lean towards paying for the backup service with a rating of 9 telling us you would definitely pay for the back-up service. A rating of 4 or lower indicates you would be less likely to pay for the backup service, with a 1 telling us you would definitely not pay for the backup services. A rating of 5 indicates you are unsure about paying for the backup services. You should rate each option as if each option was the only one presented. Please, note that it is possible to rate several situations with the same rating.

Situation 1	
Description of Outage	Occurs during winter at 6 a.m. on a weekday and last for 8 hours.
Number of outages	4 per year
User fee charged	\$50
Willingness to Pay for the Back-Up Service:	

☐ Definitely Not pay

☐ Less Likely to pay

☐ Unsure

☐ More Likely to Pay

☐ Definitely Pay

1

2

3

4

5

6

7

8

9

For each choice task, we asked respondents to rate each of the choice experiments based on their intention of paying for the back-up service on a scale of 1 to 9 (1=definitely not pay for backup services and 9=definitely pay for backup services). The rating score that a respondent chooses reveals the preference for backup power services under different conditions, with higher preferences resulting in a higher score. We used a rating scale because it allows for interpersonal comparison, and it also gives more information on the utility gaps between the rating scores (Baarsma and Hop 2009). We selected a 9-point scale to have a neutral point where respondents are indifferent, based on previous literature (Asioli et al. 2016; De Andrade et al. 2016). See Figure 2.2 for an example of the duration power outage task (one-time power outage) and Figure 2.3 for an example of the frequency power outage task (multiple power outages).

4.2 Survey

The survey data was collected using an online survey administered in Qualtrics with samples purchased from Qualtrics, Dynata, and Toluna, who were contracted to conduct the online survey. Multiple online samples were utilized to increase the number of respondents from rural and micropolitan areas. The study cover states across the Great Plains and covers both Metropolitan Statistical Areas (MSAs) and Non-Metropolitan Statistical Areas (N-MSAs), which were our targeted populations. We received 3,673 completed surveys across the study region. However, we excluded 151 observations which failed 2 or more quality checks, which included (1) if the respondent answered the survey in less than 7 minutes (speeding check); (2) missed all the CAPTCHA questions that were designed to check for attention, and/or (3) if the respondent had answered the same answers for all options in 5 or more question blocks that had more than 3 questions. These methods are used to reduce hypothetical bias and help ensure quality data (Penn

and Hu 2021). The resulting survey dataset used for the study had an overall sample size of 3,522 observations after taking account of the quality checks. Surveys were collected from Texas (25.24%), Kansas (21.21%), Oklahoma (22.66%), Nebraska (14.65%), Colorado (9.51%), and Iowa (6.73%), with the sample size of each state in brackets. The survey overall collected information on household demographics and characteristics; renewable energy support and perceptions; renewable energy adoption; values, beliefs and norms; energy use and insecurity; energy resilience and the power outage choice experiment detailed here for this study.

Table 2.3 provides descriptive statistics for selected demographic variables. We provide the mean and standard deviation for the entire sample and means for each statistic from the U.S. Census when available. Census averages represent a population-based weighted average across the states being surveyed. The sample differed from the census averages for the median yearly income, median age, average race, and those with a college degree. The census median age, yearly income, and household size were 37 years, \$76,049, and 4.97, respectively. In our study, the median age was 50 years, and the average yearly income was \$70,685, with a median yearly income of \$62,500. Census statistics indicate 76% of the population in the area is white, and 35% of the population has a college degree. In our survey sample, 87% of the sample population were white, and 53% had a college degree. The difference could be due to the sampling frame; we restricted our sample to having 50% of the respondents coming from Metropolitan Statistical Areas (MSAs) and the rest from Non-Metropolitan Statistical Areas (N-MSAs). Other demographic characteristics of the sample are that female-headed households comprised 36% of our sample and on average, households had 5 persons living in the household.

Table 2.3. Summary of Dependent and Demographic Variables

Demographic Variables	Census		All respondents
Variable	Percent of Population	N	Percent of Population
College Degree or Higher	35.2	3506	53
Female Headed Households	-	3447	36
White	76	3462	87
	Mean	N	Mean (Standard Deviation)
Households Size	2.50	3518	4.97 (3.60)
	Median	N	Median
Age	36.64	3518	50.0
Median Yearly Income	\$76,049.2	3452	\$62,500

5. Results

We present results for the duration and frequency power outage tasks, followed by the combined analysis of examining WTP when considering changes in both duration and frequency. In addition, we conduct a number of robustness checks: (1) comparison of model to estimates to a separate model based on a weighted utility based on Baarsma and Hop (2009) method that assumes respondents attach the same mean rating for the average reliability of power supply in any choice task, (2) examination of changes in the base duration for the frequency outage task, and (3) specification of linear and quadratic functions of duration and frequency instead of the logs; and (4) inclusion of household characteristics and demographics in the RPLM.

5.1 Duration Power Outage Sub-Utility Random Parameter Linear Model

5.1.1. Estimation Results and Robustness Checks

In Table 2.4, we show the estimation results for the duration power outage RPLM following Equation (17). The duration outage model captures household preferences for paying for a back-up service to avoid a single power outage that is a function of duration, season, time of day, and time of week attributes and a user fee. Recall, the duration enters nonlinearly in the regression as

lnD. As a robustness check, we did examine a linear and quadratic specification of duration, as well. The model with a linear specification of duration did not converge. For the quadratic specification, the natural log specification was a better fit than the quadratic specification.¹⁷ Statistically significant attributes included the natural log of duration, weekday, afternoon, evening, winter, and user fee. The standard deviations of the random parameters for all of the attributes and levels, except for winter, were all statistically significant, providing evidence of heterogeneity in preferences across households for the different choice attributes. Preference for backup power services increased as duration increased, but in a nonlinear fashion. Given the natural log specification and positive coefficient, preference for the backup service increases, but at a decreasing rate. On average, respondents were almost twice as likely to prefer backup power services for an outage that happens in the evening relative to an outage during the morning. No significant difference in preferences was observed on average between a power outage in the morning and at night. Results suggest respondents had lower preferences for backup services for an outage that happens on a weekday compared to one that happens on a weekend. In addition, there was a higher preference for back-up power options during an outage in the winter, and this was relatively stable across households. Finally, preferences for back-up services decreased with an increase in the user fee charged, following demand theory.

Table 2.4. Estimated Results of Random Parameter Linear Models for the Duration and Frequency Power Outage Tasks

¹⁷ Both the AIC and log likelihood for non-linear model were lower than for the natural log specification. The AIC and log likelihood for the quadratic model were 64648.34 and -32305.17 respectively.

	Duration Power Outage Model		Frequency Power Outage Model	
	Mean of Parameter Distribution	Standard Deviation of Parameter Distribution	Mean of Parameter Distribution	Standard Deviation of Parameter Distribution
Variables				
ln Duration	0.511*** (0.011)	0.196*** (0.017)		
Weekday	-0.062* (0.036)	0.573*** (0.082)		
24-hour Base category			0.298*** (0.067)	
ln Frequency			0.150*** (0.013)	0.234*** (0.031)
Morning at 6:00 a.m.	0.071 (0.049)	0.428** (0.1731)		
Afternoon at 10 a.m.	0.099** (0.048)	1.06e-06 *** (0.0003)		
Evening at 4 p.m.	0.169*** (0.049)	0.541*** (0.143)		
Winter	0.237*** (0.035)	0.100 (0.366)		
User Fee	-0.009*** (0.000)	0.005*** (0.000)	-0.010*** (0.000)	0.008*** (0.000)
Constant	4.638*** (0.057)	1.372*** (.030)	6.197*** (0.048)	1.718*** (0.028)
Log-Likelihood	-32158.527		-31186.762	
Observations	14,088		14,088	
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

In Appendix B, we present the results for the model formulation used by Baarsma and Hop (2009). Their model only assumed a random intercept, which was corrected prior to estimation of their model. Comparing the two models, we observed a small difference in the values of all coefficients and a change in significance level for some of the attributes. In the RPLM, except for the morning and evening levels of the time of day attribute, the attribute coefficients were slightly bigger than those estimated using the model specification following Baarsma and Hop (2009). In the RPLM, we observed an outage in the weekday to be significant, no difference in preferences

between an outage in the morning and at night, and that respondents attached more value to an outage in the afternoon relative to a night-time outage, which was different from results using the Baarsma and Hop (2009) model. Another difference between the two models arose from the significance level of the standard deviations of the RPLM parameter distributions, which showed that there does exist unobserved heterogeneity not only in the constant term, but also in the slope coefficients (or marginal sub-utilities) for the attributes and levels. Thus, our results also show that there may be some bias when using the Baarsma and Hop (2009) empirical estimation approach when assuming the marginal utilities for power outage attributes are not random.

Although the study by Baarsma and Hop (2009) finds that social and economic variables included in the regression have no statistically significant effect on the ratio of the coefficients of duration and frequency to changes in the electricity bill, we carried out the same sensitivity analysis as an additional robustness check¹⁸. See Appendix B for full estimation results. We included the following household-level explanatory factors in the model to assess this assumption: household income, household size, house ownership, number of years the households has lived in the area, if the households has a medically electric dependent person living in the households, if the household is located in a Metropolitan Statistical Area (MSA), if the household has a backup energy source, and if the household has been affected by a power outage in the recent past. In the duration power outage model, including household characteristics and demographics in the RPLM did result in changes in the value and significance levels for some parameter distributions. The preference for backup services during the weekend was no longer statistically significant compared to weekdays.

¹⁸ The ratio of the coefficients of duration and frequency did not change. It is 3.4 for a model with and without household characteristics and demographics.

The parameter distribution coefficients for the duration attribute changed, but the change in magnitude was -0.001. The coefficients for all the household characteristic explanatory factors were positive and statistically significant, except for house ownership, which was not statistically significant. The number of years living at their current location had a negative effect on preference, which may result from being familiar with the area and having a predetermined expectation of the chances of severe weather happening, making them less interested in backup power services. Including household characteristics and demographics adds information but did not change the main findings in the study.

5.1.2 WTP results for Duration Power Outage Model

We used the household coefficients of the duration power outage model and the estimated household D_0 to estimate households' WTP for the backup power service for varying power outage durations during a severe weather event or natural disasters following Equation (7). The WTP values are shown in Table 2.5. Except for a 1-hour outage, all the other power outages had a positive WTP. A WTP of \$-88.54 for the one-hour outage provides evidence of disinterest in the backup services, and you have to pay respondents to use the backup services, which we assume is zero for actual purposes.

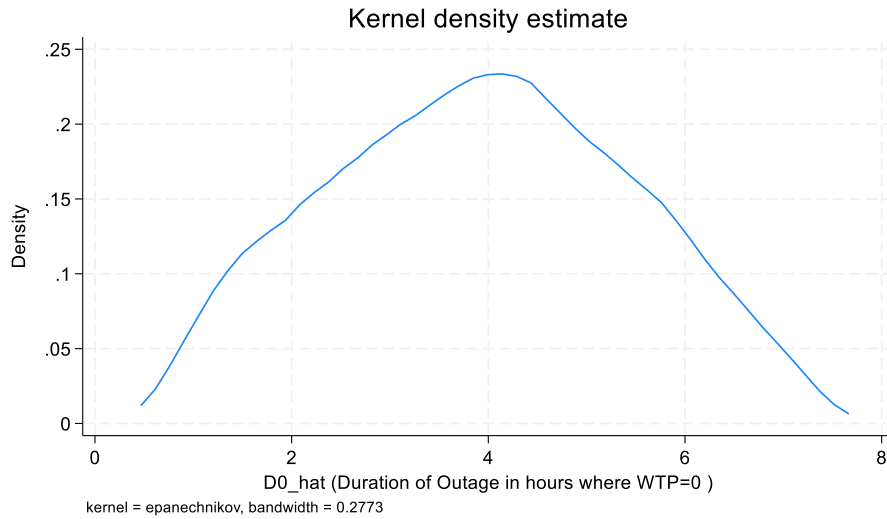
Table 2.5. WTP Per Event for Power Back-up Services for Various Durations and Frequency of Severe Weather Power Outages

Random Parameter Linear Model		
Duration of Outage (One per year)	Mean WTP (\$)	Marginal WTP (\$)
1 hour	-88.54	-
4 hours	3.82	1.27
8 hours	50.00	11.55
24 hours	123.20	4.57

72 hours	196.39	1.52
120 hours	230.43	0.71
Number of outages (of 8 hours)		Marginal WTP (\$)
1 every 10 years	18.04	-
1 every 5 years	26.43	8.39
1 every other year	39.38	4.32
1 per year	50.00	2.12
2 per year	60.99	1.10
4 per year	72.17	0.56
Average D0 (hours)		3.92

D_0 in Equation (13) is the duration of power outage that is acceptable to households in which the WTP is zero ($P_0 = 0$). D_0 varies across households, as illustrated in Figure 2.4. The kernel density estimate in Figure 2.4 is estimated using household-specific parameter estimates from the RPLM (Table 2.4). The kernel density shows estimates of D_0 between the 5th and 95th percentiles of household-specific parameter estimates for D_0 , which range between 0.73 hours and 7.06 hours, respectively. We did this to remove outliers. The mean across households D_0 is estimated to be 3.92 hours. At this estimate, the mean WTP by households is still slightly negative but close to zero.

Figure 2.4. Kernel Density Estimate of the Distribution of $\widehat{D}_0$ for Random Parameter Linear Models for Duration Outage



We estimated the mean WTP for the back-up service to avoid a power outage or value of lost load using the methods outlined in the empirical model section. In estimating the means, we used household-specific WTP values that fell between the 5th and 95th percentiles of the household-specific WTP estimates from the RPLM to remove outliers that were extremely high or low. Including these outliers resulted in significant bias in the mean WTP values estimated in Table 2.5, which has been shown to be a challenge when estimating Random Parameter Linear Models (Hensher et al. 2015). We find that the mean WTP for a backup power service increases with the duration of outage (H1a) (Table 2.5). Based on the RPLM, on average, respondents are WTP \$3.82 to avoid a 4-hour outage, \$50.00 to avoid an 8-hour outage, \$123.20 to avoid a 24-hour outage, \$196.39 to avoid a 72-hour (3 day) outage, and \$230.43 to avoid a 120-hour (5 day) outage for a single event. We also see that on the margin as duration increases, respondents are WTP more at a decreasing rate after 8 hours. When we average the WTP values across households and compare the results to those using the Baarsma and Hop (2009) model, a similar trend was also obtained (see Appendix Table B.2). However, the WTP results were lower than those estimated using RPLM, see Appendix Table B.2. The difference increased with an increase in duration of outage.

For example, the mean difference in WTP between the RPLM and Baarsma and Hop (2009) model to avoid a 120-hour outage is \$26.22 and \$0.01 for a four-hour outage.

The WTP values based on the RPML for the various durations of outage when household socio-economic factors are added into the model do slightly change, but the effect is minimal for power outages that last less than 24 hours and is slightly higher for power outages that last more than 72 hours or 3 days. Recall, WTP is estimated using the pricing equations from the conceptual model, which depend primarily on the coefficient distributions on the natural log of power outage duration and user fee. Given that these parameter distribution estimates do not differ much when the additional factors are included, differences in WTP values are relatively small and do not change the primary findings in the study. As the duration of a power outage increases, WTP increases even with the inclusion of household characteristics and demographics. On average, respondents are WTP \$5.69 to avoid a four-hour outage, \$50.08 to avoid an eight-hour outage, \$120.43 to avoid a 24-hour outage, \$190.78 to avoid a 72-hour outage, and \$223.49 to avoid a 120-hour outage that happens once a year, which are very close to the estimated mean WTP values in Table 2.5.

5.1.3 Marginal WTP for Other Power Outage Attributes

We estimate the marginal WTP for the other power outage attributes and levels empirically from the RPLM following methods in the literature as the negative of the ratio of the attribute coefficient to the coefficient of the user fee at the household level. On average, households were willing to pay \$30.84 more to avoid a severe winter weather power outage relative to a summer outage. A nighttime outage at 10 p.m. was valued less than any other severe weather outage time. On average, households were WTP \$9.50 more to avoid a morning outage at 6 a.m., an additional \$12.80 to

avoid an outage in the afternoon at 4 p.m., and an extra \$22.21 to avoid an evening outage at 4 p.m. relative to a nighttime outage at 10 pm. As for time of week, an outage on the weekend was valued less than an outage on a weekday. On average, households were WTP \$5.86 more to avoid a severe weather outage on a weekday compared to the weekend. All the marginal WTP for the power outage attributes were significantly different from zero, except for the marginal WTP between a power outage in the morning and night.

5.2 Frequency Power Outage Sub-Utility Random Parameter Linear Model

5.2.1 Estimation Results and Robustness Checks

In Table 2.4, estimation results are provided for the frequency power outage RPLM with frequency and user fee as the two continuous attributes. We used a logarithmic specification for frequency because the relationship between this variable and rating score is likely non-linear. When examining a quadratic functional form for frequency, the estimation process did not converge. For a linear specification, the natural log specification had a better fit than the linear model¹⁹. In the frequency model, a dummy variable for the choice of base category to control for the base duration effect was included. The base category was either 8 hours or 24 hours. The dummy variable was set equal to 1 if the base was set at 24 hours and 0 for 8 hours. For robustness, we also estimated a separate model that included two interaction terms to assess if the base category had a direct influence on the effect of frequency of an outage or user fee. The two interaction terms included the natural log of frequency and the 24-hour base category, and the user fee and the 24-hour base category. Neither interaction term had a statistically significant influence on preferences for a

¹⁹ The AIC and log likelihood for the linear model are 62368.76 and -31176.38, respectively.

back-up service or on the effect of frequency or user fee. Thus, we did not include the interaction terms in the final model. The coefficient in the 24-hour base category was statistically significant, indicating a stronger preference for back-up services with a longer base duration. Given that the interactions were not statistically significant, the pricing equations used to estimate WTP in the conceptual framework are not impacted by the choice of base category. This provides the needed evidence to estimate the pricing equations as derived in the conceptual model, which Baarsma and Hop (2009) did not verify empirically. This helps support the weak separability assumption made and the functional specification of the model.

Respondents are more interested in backup power services as the frequency of outages increases, and less interested when the user fee increases, following expectations. We observed that all the standard deviations of the random parameter distribution in the RPLM are highly significant, indicating there is heterogeneity of preferences amongst households for the different model attributes. As expected, we observe similar signs in all the coefficients when we compare the model specification following Baarsma and Hop (2009) and our estimated RPLM. See the Appendix B for estimation results for the model formulation following Baarsma and Hop (2009). The only small difference in the value of coefficients between the two models was the dummy variable for the 24-hour base category. This may result from the use of different measures for the dependent variable.

We also conducted an additional robustness check for the frequency of power outages RPLM by including household characteristics and demographics, following what was done with the duration of power outages RPLM. We observe that in the RPLM, inclusion of different household explanatory factors does not change the statistical significance for the frequency and

user fee attributes. Differences are relatively small for both the parameter and standard deviation estimates for the random parameters (See Appendix B). Some of the positive and statistically significant household characteristics and demographics included household income, household size, whether the household has a member who was electric dependent for health reasons, if the household is located in a Metropolitan Statistical Area (MSA), homeowners compared to other types of house tenure apart from renters²⁰, and if the household has been affected by a recent power outage. Negative and statistically significant variables included the number of years the household has lived in the area. As before, the longer the number of years, the less likely the households are interested in backup power services.

5.2.2 WTP results for frequency Power Outage Model

We estimated the WTP of households for backup service to avoid alternative frequency levels of power outages at a given base duration of length during severe weather events, following methods outlined in the conceptual and empirical sections above. The WTP estimates capture households' WTP for a backup power service for various frequency levels at a duration of an 8-hour outage (H1b) or value of lost load at different frequencies. For WTP estimation, we include only household-specific values of WTP that fall between the 5th and 95th percentiles of all estimates, to remove outliers that were extremely high and low, which could bias mean WTP estimates²¹. Mean

²⁰ We re-estimate the model with homeowners as the base, and there is no significant difference between homeowners and renters.

²¹For example, without restricting WTP values to fall between the 5th and 95th percentiles, the minimum WTP to avoid an outage that happens four times per year is \$-10,328.83 per event and a maximum of \$13,116.40 per event but it is a minimum of \$3.85 per event and a maximum of \$478.33 per event if we restrict the WTP to fall between the 5th and 95th percentiles of all estimates.

WTP values for the frequency power outage task are provided in Table 2.5. Mean WTP across households increases with an increase in frequency of outages. Respondents on average are WTP \$18.04 per event to avoid an outage every 10 years, \$26.43 per event to avoid an outage every 5 years, \$39.38 per event to avoid an outage every other year, \$50.00 per event for one outage per year, \$60.99 per event to avoid an outage that happens two times per year, and \$72.17 per event to avoid an outage that happens four times per year. On the margin, as outage frequency increases, respondents are WTP more at a decreasing rate. Similarly, WTP based on model estimation following the Baarsma and Hop (2009) specification shows an upward trend in WTP as the frequency of outages increases, but the values are lower than those from our RPLM (see Appendix B). The mean difference in WTP between RPLM and Baarsma and Hop (200) to avoid an outage that happens four times per year is \$7.73 and \$1.93 per event for an outage that happens once every 10 years.

The WTP values based on the RPLM for the various outage frequencies are slightly lower when household and socio-economic factors are directly included in the model, but changes in parameter estimates are relatively small, and main findings do not change (see Appendix B). The WTP values when we include socio-economic is \$17.63 per event to avoid an outage every 10 years, \$25.83 per event to avoid an outage every 5 years, \$38.49 per event to avoid an outage every other year, \$48.86 per event for one outage per year, \$59.60 per event to avoid an outage that happens two times per year, and \$70.53 per event to avoid an outage that happens four times per year.

5.3 WTP for Various Power Outage Duration and Frequency Combinations

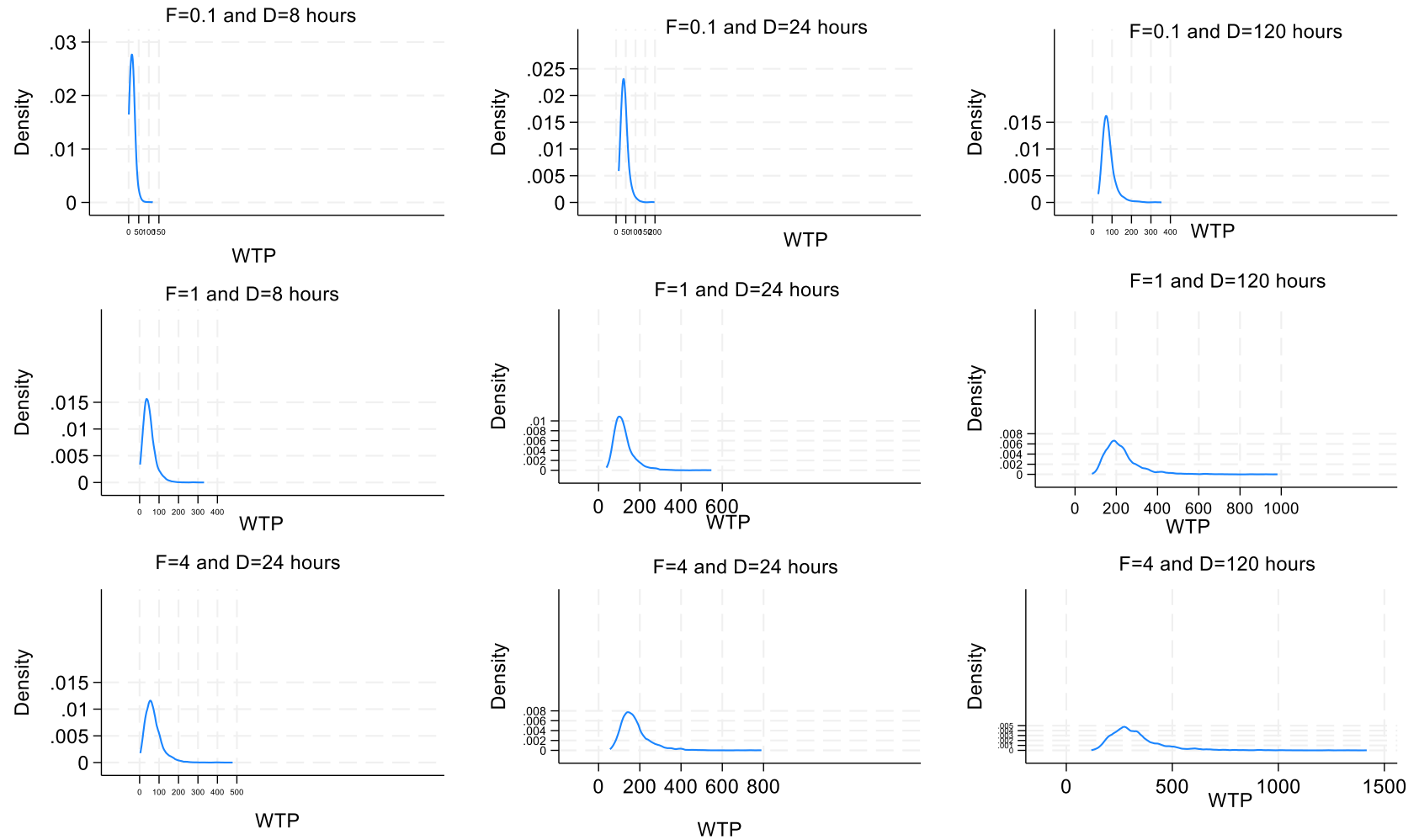
In this section, we examine how WTP values change when both power outage frequency and duration vary (Hypothesis H1c). Respondents were WTP to pay more when both frequency and duration of outage increased, but this depended on the acceptable level of frequency and duration by the household. Recall there are four possible scenarios that could be examined that look at various frequency (F) and duration (D) combinations based on changes from F_0 and D_0 . F_0 is the least number of power outages technically possible, which was assumed to be $F= 0.05$ (1 severe weather power outage every 20 years). D_0 represents the duration of outage that is acceptable to households in which the WTP for back-up services to avoid the outage is zero, which varies across households. As with WTP estimation above, when calculating means and examining changes using household-specific estimates of WTP, we only include values that fall between the 5th and 95th percentiles to remove outliers that were extremely high or low.

5.3.1 Scenario 1: Power Outage of Duration $D > D_0$ for a Given Outage Frequency $F > F_0$

Equation (15) was used to estimate household-specific WTP values for power outages in Scenario 1. All WTP values under this scenario were positive. The distributions of household-specific WTP estimates at various power outage durations and frequencies for Scenario 1 are presented in Figure 2.5. We observe a lower WTP value at a lower frequency of outages compared to a higher frequency. For example, the minimum household WTP for an 8-hour outage that happens once every 10 years is \$0.96 per event, with a maximum WTP of \$119.59 per event and a mean of \$18.04 per event. For an 8-hour outage that happens 4 times a year, the minimum WTP was \$3.85 per event, with a maximum of \$478.35 per event, and a mean of \$72.17 per event. We also observe that a change in frequency has a much larger effect on WTP values compared to duration. As you

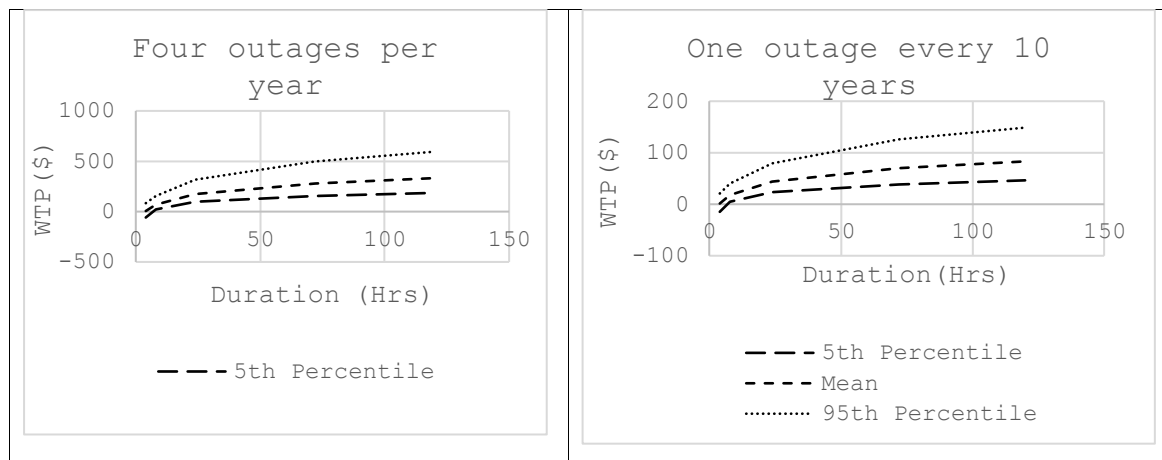
look top to bottom for a given column in Figure 2.5, WTP values become larger much faster and more widely distributed as frequency increases relative to changes in duration (when looking across a row, left to right). The distribution of WTP values changes more when considering frequency relative to changes due to duration, especially for higher outage frequency levels. It may be that, as power outage becomes frequent, one needs to account for household characteristics and demographics, which should be further explored in future research.

Figure 2.5. WTP Values Per Event at Various Combinations of Frequency (F) and Duration (D) when $D > D_0$ and $F > F_0$ for Random Parameter Linear Model



We examined WTP values at various frequency levels and duration at the mean, at the 5th and at the 95th percentiles across household-specific WTP estimates in Figure 2.6. Only two frequencies are displayed in Figure 2.6: one outage every 10 years and 4 times per year²². Differences in WTP between the mean WTP and the WTP at the 5th and 95th percentiles exist and can be substantial. For example, the mean WTP for a 120-hour outage that happens four times a year is \$332.60 per event, while the WTP at the 5th and 95th percentile is \$185.71 and \$594.97 per event, respectively. This shows that at any given level of frequency of outage, the WTP for backup services is sensitive to the duration of outage, and the variance in WTP values increases with duration.

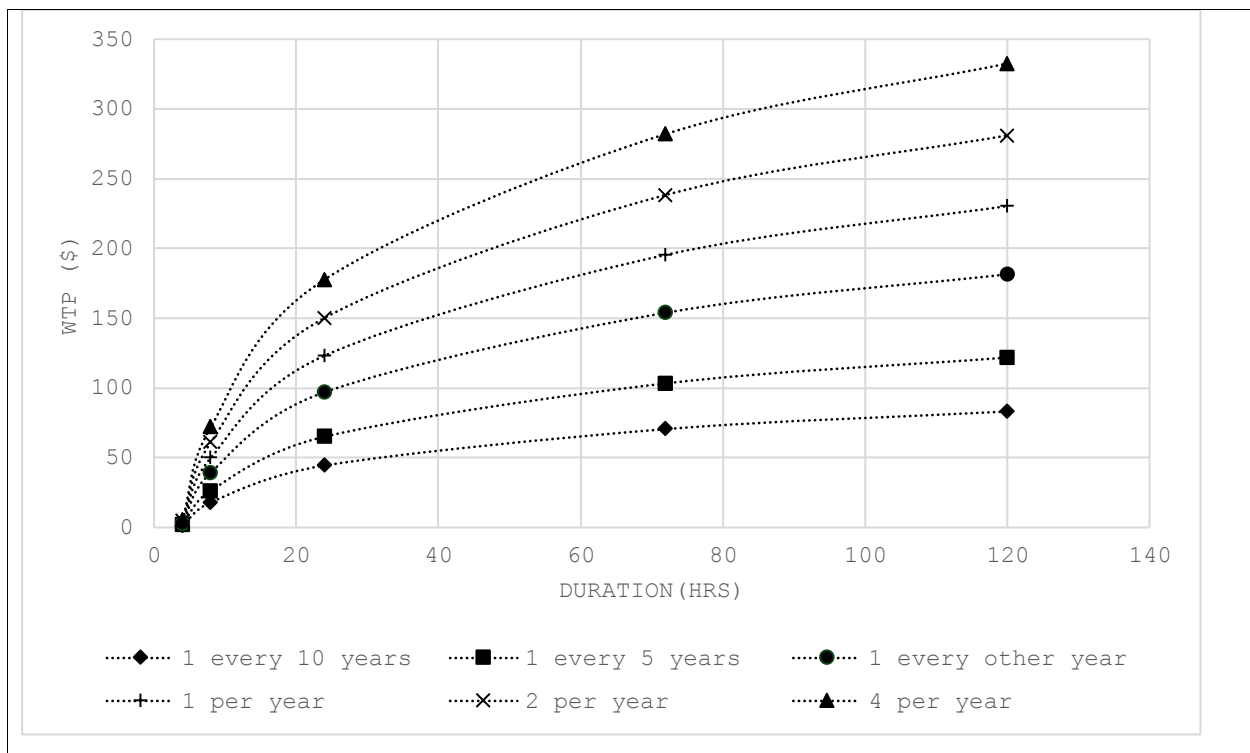
Figure 2.6. The WTP Values Per Event at Various Frequency Levels and Duration at the Mean, at the 5th and 95th Percentiles Across Household-specific Estimates



²² An increase in frequency, shifted the curve upward reflecting an increase in WTP values as frequency increased. We also observe the same trend in the difference between mean WTP value and the 5th percentile WTP value and for the difference between the 95th percentile WTP value and the mean WTP value across the other frequency levels i.e. $F=1$, $F=0.2$, $F=0.5$, and $F=1$. Both differences increased as the duration of outage increased.

Figure 2.7 shows the mean WTP for the RPLM across household-specific estimates for different frequency and duration combinations. Compared to values based on Baarsma and Hop (2009) model, the WTP values are much higher, and the WTP curves are less steep (See Appendix B). The mean WTP across households estimated with the RPLM is \$1.38 per event to avoid a 4-hour outage that happens once every 10 years and \$332.60 per event for a 120-hour or 5-day outage that happens four times a year. This is compared to \$ 1.37 and \$294.75 per event for the same outage-frequency combinations estimated following Baarsma and Hop (2009), respectively (see Appendix). We observe the highest difference in WTP values between the RPLM and Baarsma and Hop (2009) model at the 4-hour duration of outage, and estimating WTP values at the household level may be driving the mean WTP up, which decreases with an increase in duration of outage.

Figure 2.7. The Mean WTP Values Per Event for Severe Weather Power Outages when $D > D_0$ and $F > F_0$ for the RPM



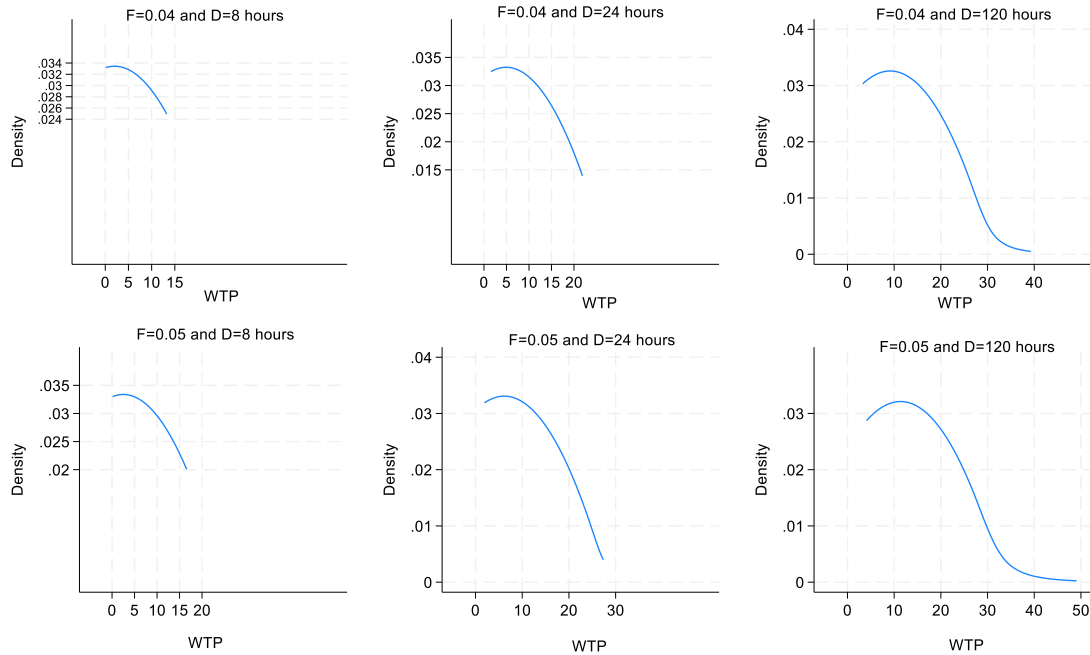
5.3.2 Scenario 2: Power Outage of Duration $D \leq D_0$ for a Given Outage Frequency $F > F_0$

The user fee households are WTP for a power outage of duration $D \leq D_0$ for a given outage frequency $F > F_0$ is equal to zero. This is because respondents are not WTP anything for outages below D_0 .

5.3.3 Scenario 3: Power Outage of Duration $D > D_0$ for a Given Outage Frequency $F \leq F_0$

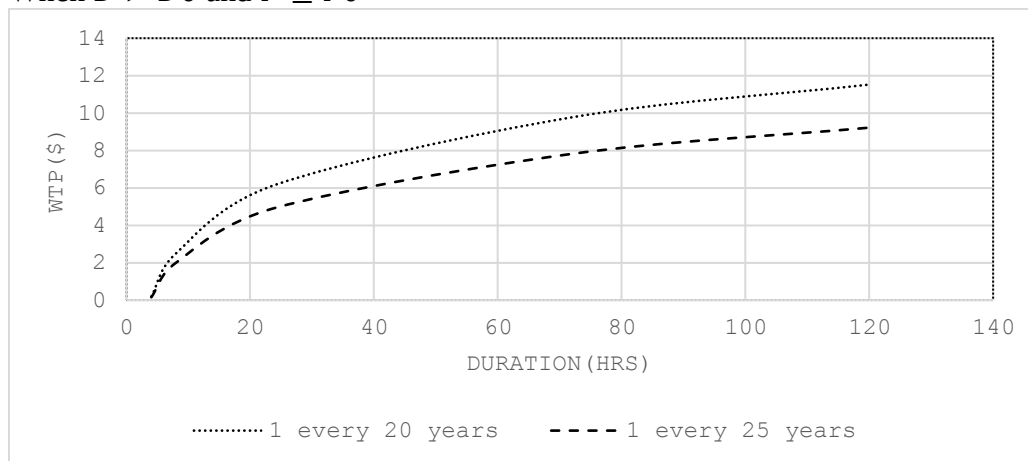
The user fee Households are WTP for severe weather power outage of duration $D > D_0$ for a given outage frequency $F \leq F_0$ is positive and not directly influenced by frequency (see Equation (16)). Estimated distributions of household-specific WTP estimates across different frequencies and duration combinations are provided in Figure 2.8. We see that the distribution of WTP shifts more to the right with a longer tail to the right as the duration of the outage increases. However, at low frequencies of outage, the effect of duration on WTP is lower. The same is also observed for frequency when the duration of the outage is lower.

Figure 2.8. Distributions of Household-specific WTP Values Per Event at Various Combinations of Frequency and Duration when $D > D_0$ and $F \leq F_0$



The mean WTP values across households are shown in Figure 2.9 at two different frequencies less than F_0 . At low durations of outage, WTP is not very different between the two frequencies examined. At lower outage durations, WTP for an outage that happens every 25 years is slightly higher than an outage that happens every 20 years. Afterwards, an increase in duration of outage increases the difference between the two outages and slowly becomes more pronounced as duration increases.

Figure 2.9. Mean WTP Values Per Event Across Households for Severe Weather Power Outages When $D > D_0$ and $F \leq F_0$



5.3.4 Scenario 4: Power Outage of Duration $D \leq D_0$ for a Given Outage Frequency $F \leq F_0$

The user fee Households are WTP for severe weather power outage of duration $D \leq D_0$ for a given outage frequency $F \leq F_0$ is zero. We know that households are not WTP when the duration is less than D_0 .

Varying both the frequency and duration of outage while including household and socio-economic factors in the model does result in some differences. Mean WTP values across households are either lower or higher depending on the duration of the outage, but the differences are relatively small. All the outages have a similar trend, and the additional factors increase mean WTP for outages of duration 4 hours, 8 hours, and decrease WTP for outages of 24 hours, 72 hours and 120 hours, irrespective of the frequency of outage. See Appendix B for the WTP values for various frequency and duration combinations for the various outages in this context.

5.4 Comparing Results with Literature

In order to estimate the WTP values for various frequency and duration levels we used the coefficients from two RPLM for the duration and frequency power outage tasks. The coefficients are also used to calculate the acceptable duration₀. The WTP value, also known as value of lost load (VoLL), provides a way to measure the indirect cost of a power outage based on the value of having the backup power. Our findings are for severe weather events and natural disasters, where most studies are for general power outages, or they do not specify the specific context. These studies also assume the acceptable duration of outage is constant across households, but in our study, we compute D_0 for each household. We find that D_0 varies across households; it ranges from 0.73 to 7.06 hours, with a mean of 3.92 hours.

In the duration outage task, we included duration, season, time of day, time of week, and user fee as attributes of severe weather power outages to determine the effect of these variables on the WTP for backup power services. The coefficients from the duration and frequency outage tasks are used to estimate the WTP values for various frequency and duration levels. The WTP values measure the indirect cost of a power outage based on the value of having the backup power. The significant attributes for the duration outage task included duration, an outage in the afternoon and evening compared to a night-time outage, during a weekday, in winter, and user fee. Comparing these results to the literature, we find that respondents are more likely to choose or purchase a backup power service that offers a lower duration of outage (Meles et al. 2021; Carlsson et al. 2020; Carlsson and Martinsson 2007; Pepermans 2011; Zemo et al. 2019; Breit et al. 2016; Abdullah and Mariel 2010). However, interest in backup power services fades with an increase in the service fee (Meles et al. 2021; Pepermans 2011; Morrissey et al. 2018; Zemo et al. 2019; Breit et al. 2016; Wen et al. 2022; Abdullah and Mariel 2010; Hensher et al. 2014). Thus, our results generally agree with the findings of similar studies in the literature.

We find that the sign and significance of the season, time of day, and time of week attributes do vary in the literature. In studies such as Pepermans (2011) and Morrissey et al. (2018), respondents were more interested in power services during the summer compared to the winter season, while for other studies, it was the opposite. This may be due to the timing of the survey and geographical location (Küfeoğlu and Lehtonen 2015a; Ozbaflı and Jenkins 2016). The first two studies were done in Belgium and England, while the last two were in Finland and Cyprus, respectively. In the US, respondents were WTP to pay more to avoid an outage in the winter compared to a summer outage (Lawton et al. 2003), similar to what we observed in our study.

Similar findings to our study were also observed in the literature, where respondents preferred not having power outages on weekends over weekdays (Carlsson and Martinsson 2007; Zemo et al. 2019; De Nooij et al. 2007; Blass et al. 2010; Hensher et al. 2014; M. Sullivan et al. 2018). Weekends are a leisure time for most households, and this is the period in which most people are at home, the same as evening hours on weekdays (De Nooij et al. 2007; Hensher et al. 2014; Baarsma and Hop 2009). Also, an outage that happens during the night at weekends is often the most costly to consumers in terms of lost activities or leisure (M. Sullivan et al. 2018). As for the time of day, the cost is highest in the evening hours (4 pm–11 pm), followed by noon (10 am–4 pm), then morning hours (5 am–10 pm), and lastly at night (11 pm–5 am) (Küfeoğlu and Lehtonen 2015a). According to Sullivan et al. (2018), household respondents prefer not to have an outage in the late evening/ early morning, followed by morning hours (7 am-11 am) and evening hours (5 pm- 8 pm) that are valued the same and lastly afternoon hours (12 pm-4 pm). However, a study by Meles et al. (2021), respondents did not prefer an outage in the morning hours compared to an outage in the daytime or nighttime. In our study, we observed that respondents preferred to pay for power services in the evening at 4 pm and an afternoon outage at 10 am compared to a nighttime outage at 10 pm, and there was no difference in preference between a morning outage at 6 am and a nighttime outage at 10 pm. The difference across studies may arise from differences in how the timing is captured, the type of outage, and the area may play a role in the difference, too.

The preference for alternative power sources increases with the duration and frequency of the outage (Zemo et al. 2019; Hensher et al. 2014; Amador et al. 2013; Meles et al. 2021; Ozbaflı and Jenkins 2016; Carlsson and Martinsson 2007; Carlsson et al. 2020; Pepermans 2011; Abdullah and Mariel 2010), similar to the cost of an outage (M. Sullivan et al. 2018; Küfeoğlu and Lehtonen

2015a). The WTP values vary across the choice of econometric model, as we observe in our study, similar to other studies such as Carlsson and Martinsson (2007) and Morrissey et al. (2018). Although we observe marginal WTP increases per hour with an increase in frequency of outage, but for duration marginal WTP per hour peaks at 8 hours and declines as the duration of outage increases. Other studies have observed marginal WTP declines continuously with both an increase in per unit duration and frequency (Blass et al. 2010; Morrissey et al. 2018) while others observed the same results (Carlsson and Martinsson 2007; Carlsson et al. 2011). The difference between studies may be explained by the difference in geographical area. It may be that different areas have different acceptable levels of duration and frequency based on the reliability of existing power services; hence, an improvement in power services will be valued differently.

In our study, we only compute the WTP values for severe weather events that vary in frequency, duration and both frequency and duration. There is no direct comparison of our WTP estimates to other existing literature, as none of the studies reviewed was based on power outages during extreme weather events or natural disasters. That is, they are not set to be context specific. For example a study by Lawton et al. (2003) found that households were WTP on average \$6.9 to avoid an hour outage, \$7.14 to avoid a four hour outage, and \$5.15 to avoid an eight-hour outage, while a study by Chowdhury et al. (2004) found WTP on average to be \$1.12 to avoid an hour outage, \$4.49 for a four-hour outage, and \$8.98 to avoid an eight-hour outage. A recent study by Gibbons and Sergici (2024) estimates the WTP to avoid an hour outage to be \$7.03. For our study, the estimated mean WTP was \$3.82 to avoid a four-hour outage, \$50.00 to avoid an eight-hour outage, and to avoid an hour of outage, it was \$-88.54. The negative WTP to avoid an hour's outage was because, on average, households were not WTP for back-up services for an outage of 3.9 hours or less on average.

For longer duration outages (i.e. 24 hours and longer), household WTP values were much higher. A study by Baik et al. (2020) found that households were WTP, on average, \$43 per 1-day of outage. For a 30-day power outage, the average WTP was \$252 in Los Angeles (Stock et al. 2023), \$78.44 per month in California (\$941.28 per year) (Gorman and Callaway 2024) , and \$14 per month (\$168 per year) in New York (Hotaling et al. 2021). In Texas, respondents were WTP \$30.83 to avoid a one-day outage and \$43.60 for a 3-day power outage (Gibbons and Sergici 2024). In Oklahoma, respondents were WTP an additional \$14.69 per month to increase electricity grid reliability. In our study, the average WTP across households to avoid one day of outage per year was \$123.20 for a 24-hour outage, \$196.39 for a 3-day outage, and \$230.43 for a 5-day outage. The higher average WTP values may arise from differences in the type of outage we were estimating. In contrast to the other studies, ours was framed as a result of severe weather or a natural disaster and combined frequency of outages, which may increase WTP values.

The household WTP for an outage increased with the frequency of the outage. On average WTP per outage was \$18.04 per event for an 8-hour outage every 10 years, \$26.43 per event for an 8-hour outage every 5 years, \$39.38 per event for an 8-hour outage every other year, \$50.00 per event for an 8-hour outage every year, \$60.99 per event for an 8-hour outage that happened twice per year, and \$72.17 per event for 8-hour outage that happened 4 times per year. The increasing trend in WTP when frequency increases was similar to that of Baarsma and Hop (2009) in the Netherlands, but a study by Blass et al. (2010) from Israel found households' WTP decreased with an increase in frequency of outage, with higher WTP recorded at 1-outage per season and least being 5-outages per season.

The results were much more informative when we adjusted both frequency and duration. Looking at WTP values for all durations of outages where the respondents were WTP for both a

decrease in frequency and duration, we see that the WTP values are much higher for higher frequency and duration scenarios. Respondents are WTP \$1.38 per event to avoid a 4-hour outage, \$18.04 per event to avoid an 8-hour outage, \$44.46 per event to avoid a 24-hour outage, \$70.53 per event to avoid a 3-day outage, and \$83.15 per event to avoid a 5-day outage that happens once every 10 years. For a frequency of 4 times per year, households on average are WTP \$5.51 per event to avoid a 4-hour outage, \$72.17 per event to avoid an 8-hour outage, \$177.82 per event to avoid a 24-hour outage, \$282.13 per event to avoid a 3-day outage, and \$332.60 per event to avoid a 5-day outage. Similar findings were also observed in Baarsma and Hop (2009). In situations where the frequency of outages is acceptable, e.g. if the outage happens once every 25 years, the WTP values are often less than \$10. On average, respondents are WTP \$ 9.22 per event for a 5-day outage, which shows how WTP values are sensitive to the frequency of the outages.

5.5 WTP values based on Metropolitan Statistical Areas (MSAs) and Non-Metropolitan Statistical Areas (N-MSAs)

In this section, we estimated the WTP of households for backup service across different population segments, i.e. Metropolitan Statistical Areas (MSAs) and Non-Metropolitan Statistical Areas (N-MSAs, which often include rural and micropolitan areas). First, we look at the acceptable duration of severe weather power outage D_0 in Equation (13). We find D_0 is 3.94 hours in MSA households and ranges between 0.88 and 7.61 hours. For N-MSAs households, the mean D_0 was 3.85 hours and ranged between 0.54-7.05 hours. Figure 2.10 shows the distribution of D_0 based on MSA and NMSAs. We then estimated the mean WTP for various power outage durations and frequencies for Scenario 1, following the methods outlined in the empirical model section. The results are shown in Table 2.6 and are restricted to be between the 5th and 95th percentiles of the household-

specific WTP estimates from the RPLM. MSA households were always WTP a higher amount for backup services compared to N-MSAs. The difference in WTP increases with each increase in duration of outage. Comparing WTP values across frequency levels, holding duration constant, we find that the difference in WTP between the two population segments is low at low outage frequency and increases with the frequency of outage. However, for a power outage that occurs 4 times a year and lasts 5 days, the difference is smaller than for a 3-day outage that occurs 4 times a year. For longer-duration outages, other factors beyond location may influence WTP values, such as household characteristics and demographics.

Figure 2.10. Kernel Density Estimate of the Distribution of $\widehat{D}_0$ for the Random Parameter Linear Models for Metropolitan Statistical Areas (MSAs) and Non-Metropolitan Statistical Areas (N-MSAs)

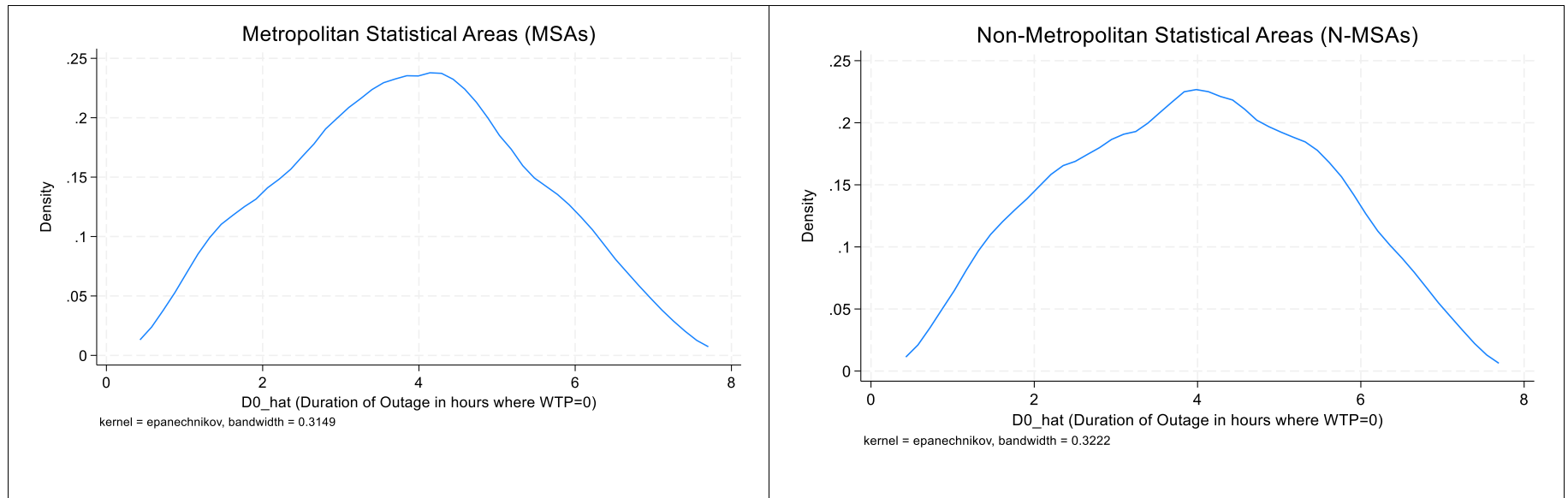


Table 2.6. Mean WTP (\$) Per Event at Various Combination Frequency and Duration Levels Based on Metropolitan Statistical Areas (MSAs) and Non-Metropolitan Statistical Areas (N-MSAs)

Frequency						
1 every 10 years				4 per year		
Duration	MSAs	N-MSAs	Difference	MSAs	N-MSAs	Difference
RPM						
4 hours	1.64	1.11	0.53	6.57	4.43	2.14
8 hours	18.49	17.58	0.91	73.97	70.34	3.63
24 hours	45.20	43.70	1.50	180.80	174.79	6.01
72 hours	71.57	69.48	2.09	272.74	267.19	5.55
120 hours	84.32	81.95	2.37	337.29	327.81	9.48

5.6 Model Application for Renewable Micro-Grid Back-Up Power Source

There are different alternative energy sources during power outages, such as energy storage and generators, and the cost of investment will be determined by the choice of an alternative energy source. For example, consider a power company that installs a 2.4 MW lithium-ion battery system that has a lifespan of 10 years in 2026 that powers 100 homes and the power company expects to recover the capital cost within 10 years, the life of the battery. The 10-year battery life span is based on expert opinion. Assume that each household consumes 1 kWh of electricity. Then the capital cost projections for 24-hour lithium-ion system is \$540,000 (\$255/kWh), \$739,200 (\$308/kWh), and \$878,400 (\$366/kWh) for low, mid, and high projections, respectively (values are in 2024\$) (Cole et al. 2025; Giraldez Miner et al. 2018). Using a mean WTP value and a mid-cost of \$739,200 and assuming we have one 8-hour severe weather outage, it will take 148 years to pay the initial cost of investment, 61 years if it happens two times a year, and 26 years if it happens 4 times a year. For a 24-hour outage, the time it takes to recover the initial cost is even lower; it is 60 years for an outage that happens once a year, 25 years for two outages per year, and 10 years for an outage that happens four times a year. See Table 2.7 for other combinations of

frequencies and duration of outage. In this application, the power company will only invest in a 2.4 MW Lithium-Ion Battery System if we have at least 4 severe weather events in a year that last 24 hours across the different cost levels.

Table 2.7. Number of Years to Recover the Capital Cost of a 2.4 MW Lithium-Ion Battery System Using WTP Values from the Study that Can Provide 24 Hour Backup Power Services

Number of Households	Duration (Hours)	Low Cost: \$540,000			Medium Cost: \$739,200			High Cost: 878,400		
		1 per year	2 per year	4 per year	1 per year	2 per year	4 per year	1 per year	2 per year	4 per year
100	4	1414	580	245	1936	793	335	2300	943	398
100	8	108	44	19	148	61	26	176	72	30
100	24	44	18	8	60	25	10	71	29	12

We observe that WTP values vary across MSAs and N-MSAs. We know that power companies will be more likely to invest in areas with higher WTP values, as they are able to recover the cost of investment faster and therefore earn more revenue. For example, if the company invests \$739,200 for a 2.4. MW Lithium-Ion Battery System that serves 100 homes and has a lifespan of 10 years, and on average, we have four 24-hour outages, it will take 10 years to recover the initial cost for investment in MSAs and 11 years for N-MSAs. In this scenario, power companies will more likely invest in MSAs creating disparity in household power resilience. To ensure equity in the distribution of power, the government needs to provide a subsidy of \$24,040 ($6.01 \times 4 \times 10$) to cover the difference in total WTP values for the ten years between MSAs and N-MSAs. See Table 2.6 for the mean household WTP values for an event.

The number and duration of severe weather outages each year are unpredictable, and the size of the Lithium-Ion Battery System invested by utility companies will be determined by the average frequency and duration of outages in an area. For the investment to be profitable, the frequency and duration of outage should fall within a certain range, as shown in Table 2.7. If the frequency and duration are fluctuating and some are not within the range, utility companies may

not invest resources in alternative sources of energy during severe weather outages or might invest in a smaller Lithium-Ion Battery System that ensures reliable revenue. For the investment on Lithium-Ion Battery System to be profitable, the government may need to subsidize the difference between the yearly fixed cost and revenue to warrant an investment. For example, if a company invests 2.4. MW Lithium-Ion Battery System that serves 100 homes, and in a given year, we have four 8-hour outages instead of four 24-hour outages; the government will be required to pay \$45,489 (73,920-28,4300) for a \$739,200 Lithium-Ion Battery System to warrant the invest for a battery that has a lifespan of 10 years. The government could incentivize the power company to invest in a bigger Lithium-Ion Battery System by partially funding the portion of the cost, depending on the projected revenue from the WTP values obtained for the use of the backup services, ensuring household resilience during severe weather power outages. The same applies to community-based energy storage. Communities can pay for the capital cost of the investment, through spreading the cost to several installments over the lifespan of the investment (10 years), regardless of the frequency and duration of outages, in cases where we have no government intervention.

6. Discussion and Conclusion

Severe weather events are the primary cause of significant power outages in the U.S. Severe weather events have increased in frequency and severity, and it's anticipated that these events will continue to increase. The U.S. has an ageing grid infrastructure that is more than 100 years old, which makes the country vulnerable to power outages caused by severe weather events and natural disasters. Adopting new and smart technologies, such as solar, smart grids and system hardening, often comes at a high cost, which must be paid by customers. In addition, it is often hard to value

the indirect costs of a power outage for a household, in terms of lost leisure activities, work time, etc. While studies do exist in trying to estimate WTP for back-up services and similar investments, it is not fully understood whether homeowners are willing to pay for such investments, as studies are piecemeal in the U.S. and across the globe. Furthermore, there exist no studies to our knowledge that examine WTP to avoid a power outage that combines both frequency and duration in the context of extreme weather events and natural disasters that often result in more significant power outage events. We used primary data from a two-stage choice experiment and a theoretically consistent framework to estimate household WTP for back-up services to avoid a power outage during a severe weather event. These estimates provide important findings on supporting investments in power infrastructure and services to improve resilience of the electric grid and how households are impacted by power outages by providing an indirect estimate of the cost households face from a power outage, often known as the value of lost load.

We see that WTP values increase with duration and frequency of outage. However, the increase in WTP per hour, holding frequency constant, is highest at a duration of 8 hours and declines afterwards. When there is an increase in frequency, holding duration constant, we see that the WTP per frequency of outage increases at a decreasing rate. Varying both the frequency and duration of outage, the WTP values are much higher, but this depends on what frequency and duration are acceptable to a household. If the duration of a given outage is acceptable ($WTP > 0$) by a household, for a given frequency level above a threshold (often based on a household's perception of fully reliable, e.g. outage once every 20 years), the household's WTP will be positive, providing evidence of households' willingness to support for ways to improve power infrastructure reliability and resilience.

The estimated household WTP values can be used by power companies for resource planning by determining if it is profitable to invest in alternative power sources, infrastructure hardening or other technologies that improve reliability and resilience. The level of investment that would be supported would be based on households' WTP for how the investment changes the reliability of power provision, in our case reductions in the frequency and duration of outages from severe weather. We observe that the WTP values increase with duration and frequency of outage, and the power companies can use this information to determine which areas are in dire need of alternative power sources and to better target restoration efforts after an outage. The set price should be equal to or less than collective WTP values across a region, and power companies and utilities can use this information to determine potential pricing. In some cases, electric companies may be inclined to only offer improved energy services in areas where the WTP for services is higher, such as micro-grids and energy storage options that can improve energy resilience and lessen impacts on customers from outages.

From a policy perspective, governments can use the WTP values to determine the amount of intervention/subsidy required to ensure equity in the distribution of power services, as we observe that socio-economic factors and geographical location play a role in supporting such investments and overall utility of WTP for back-up services or to avoid a power outage. In cases where the WTP values are lower than the cost of investment in backup power services, the government can use this information for policy making, to determine how much of a subsidy or grant may be required to support the investment in alternative sources of power during severe weather events to prevent financial, infrastructure, and societal impacts.

As for local communities, they can use the WTP values to determine if there is a market for backup services or investments that improve the reliability and resilience of power systems to

extreme weather events and natural disasters. Based on the WTP values, these communities can lobby for investments in alternative sources of energy, infrastructure hardening, and new technologies, amongst other options. It can be that the cost of buying and maintaining a household backup power system may be prohibitively expensive, and if an alternative community power source exists, this may be a less expensive option overall. This is an area for future research.

Further research is needed to determine if WTP values vary across various groups of households and geographies. Previous studies have shown that WTP values can vary across groups based on area, demographic, and socio-economic characteristics (J. Cohen et al. 2018; Lambert et al. 2024; Stock et al. 2023; Gorman and Callaway 2024; J. Cohen et al. 2017). Grouping respondents and calculating the WTP values can further guide policy implications. Also, we assume that the acceptable frequency of outage is one outage every 20 years and below. Estimating it at a household level will provide information on a range of acceptable frequency levels based on the occurrence of severe weather events and disasters. By knowing this, power companies and utility companies can use this information to plan for the required investment in alternative sources of energy and other investments based on the frequency of outages.

Chapter 3 - The Role of Alternative Information Sources and Channels on Disaster Perceptions and Preparedness in a Wildfire Context: A Comparison of the Great Plains and Mountainous Western States in the U.S.

1. Introduction

In the U.S., wildfires have caused significant destruction, resulting in damage to structures, property, habitats, and agricultural lands (Calkin et al. 2014; Bergtold et al. 2024). An average of 2,832,800 ha of private, state, and federal land is burned in the U.S. due to more than 73,000 wildfires each year (Forest Service. U.S Department of Agriculture, n.d.). In 2022, wildfires burned almost 2,428,114 ha in the U.S., and the area burned has increased over the past 2 years (National Interagency Fire Center 2022). Earlier studies predict that the length of fire seasons will increase and the overall frequency and severity of wildfires will grow by as much as 50 to 150% across regions of the U.S. (V. M. Donovan et al. 2017; Edwards et al. 2019; Stambaugh et al. 2017). Large wildfires (wildfires over 405 ha in size) are growing in number and intensity, specifically in the mountainous western regions (MW) and the Great Plains (GP) of the U.S. (Dennison et al. 2014; Gafford 2024; Carney et al. 2025). These changes in wildfire patterns are attributed to changes in climate, the emergence of invasive species, increased fuel loads, land management, and fragmented adoption of fire management and preparedness practices, amongst other factors (Dennison et al. 2014; Holsinger et al. 2016; Mueller et al. 2020; Keyser and LeRoy Westerling 2017; John T. Abatzoglou and Williams 2016; Holden et al. 2018). Estimates in the western U.S., including the Great Plains (GP), of potential economic damages to residential

properties caused by wildfire in high wildfire risk areas ranged from \$189 to \$444 billion in 2013 alone (Botts et al. 2013; Steelman 2016).

In the U.S., much of the focus and research on wildfires highlights the wildland-urban interface and is constituted in the mountainous western states of the U.S. (MW), both by the government and in scholarly work. From 50 to 95% of funding to help combat wildfires is spent at the urban-wildland interface (Gude and Rasker 2008). Yet, there is an increasing danger of wildfire in other areas, such as the landscapes of the Great Plains of the U.S. (GP). This region is another highly susceptible area for potential property and structural damage, which continues to receive relatively little attention (Calkin et al. 2015; Gude and Rasker 2008; Steelman 2016; Lindley et al. 2019), and yet faces significant risk. Six of the twenty fastest-growing fires in the U.S. occurred in the GP between 2001 and 2020, burning landscapes that are predominantly grasslands. These wildfires burned from 40,000 to 214,000 ha in a single day (Balch et al., 2025). For residents, this means that adequate resources and messaging about wildfire events, danger and evacuation must be extremely timely. Areas with low allocation of resources tend to face significant challenges in effectively managing and messaging about wildfires (Ermagun et al. 2025). The situation is further worsened by the inability of wildfire legislation to address the increasing severity and frequency of wildfires, which tends to be inflexible to local contexts (Gafford 2024; Steelman 2016; Buettner and Schultz 2024). Nationally, the level of disaster preparedness is low, and approximately only one-third of American households have adequate disaster plans (Petkova et al. 2016; Cook and Howe 2024). We focus here on the influence of alternative information sources on wildfire and disaster preparedness in a wildfire context in the GP and MW of the U.S.

With the increase in severe weather events and natural disasters such as wildfires, disaster preparedness education and awareness have become important in increasing disaster preparedness and resilience among households and communities (Kusumastuti et al. 2021; Armstrong et al. 2021; L. Guo et al. 2025; Kirschenbaum et al. 2017; Thomas et al. 2015; Kirschenbaum et al. 2017; C. Guo et al. 2020). Disaster preparedness increases households' resilience, enabling households to cope, recover, adapt, and coexist with severe weather events and natural disasters (Prior and Eriksen 2013; Jonientz-Trisler et al. 2025; Lindell and Perry 2000; Douglas Paton et al. 2008; Thomalla et al. 2006; Whittaker et al. 2012; Wilson et al. 2020; Kusumastuti et al. 2021). Disaster awareness, provided through different communication channels, has been shown to influence disaster preparedness and resilience at the household scale (Zhang et al., 2026). More specifically, wildfire information has been found to be critical in influencing the perception of wildfire risk and determining wildfire mitigation preparedness levels (McCaffrey, 2004). The higher the exposure to preparedness information, the higher the level of perceived disaster preparedness (Basolo et al. 2009). In turn, being prepared for a disaster, including a wildfire, has been shown to influence disaster response and impacts (e.g. health, property and financial) at the household level (Beaty et al., 2019; Clay et al, 2020; C. Guo et al., 2020).

Nevertheless, wildfire information sources vary by region, with many rural households receiving their information from television, radio, reverse 911, social media, family, and friends (Velez et al. 2017; Slavkovikj et al. 2014; Lawson et al. 2024). Thus, alternative communication channels and information sources play an important role in different contexts and geographies. A study in Oregon in the U.S. found that traditional information sources, such as television news and the National Weather Service, were the most used channels for information-seeking during wildfire season (Lawson et al. 2024). In Hong Kong and China, a study showed that both

traditional channels (e.g. radio and television), government disaster training activities, and newer information channels (e.g. official websites/apps, phone apps, and social media) all played a crucial role in household and community disaster preparedness and resilience (C. Guo et al. 2020; Zhang et al. 2026). Cretikos et al. (2008) found that broadcast media immediately before and during a storm was an important information source in influencing household disaster preparedness for the storms. Another study in Indonesia found that after an earthquake, public education and socialization channels most influenced disaster preparedness (Kusumastuti et al. 2021). Ahsan and Khatun (2020) found that community radio played a crucial role in disaster awareness and preparedness for coastal communities in Bangladesh.

The importance of communication channels in the connection between disaster preparedness and effective response can be crucial (Ahsan and Khatun, 2020). Beatty et al. (2019) empirically establish a linkage between information seeking about disaster risk and emergency preparedness. They found that forecasts for hurricanes increased sales of emergency supplies prior to landfall. The diffusion of disaster information varies across rural, suburban, and urban areas, which may influence the use and efficacy of alternative information sources (Okeukwu-Ogbonnaya et al. 2024). The number of wildfire information sources accessed by a household depends on a household's prior wildfire knowledge and experience, and previous preparedness actions (Velez et al. 2017). Wildfire information sources can further influence how much is spent on wildfire suppression, both at an individual and community level, and may also determine if a disaster-stricken area receives relief after a wildfire event (G. H. Donovan et al. 2011; Eissensee and Stromberg 2007).

Research most often focuses on factors influencing disaster preparedness education, the models and frameworks used, and the innovative approaches adopted (L. Guo et al. 2025). Studies

highlight that disaster preparedness information is most effective when it incorporates risk level, meets society's needs, clearly states recommended protective actions with step-by-step instructions, and emphasizes how to maximize individual safety and health (Abunyewah et al. 2020; Lawson et al. 2024; Kanakis 2016; Armstrong et al. 2021; Appleby-Arnold et al. 2021; Sutton et al. 2021). However, studies show that to maximize reach, disaster preparedness information should be frequent and use the most accessible communication channels. The choice of channel will depend on the nature of the hazard and local dynamics (Graf et al. 2026; Fan et al. 2019; Lawson et al. 2025, 2024; Maduz et al. 2019; Lam et al. 2017). There is a shortage of studies that compare the influence of alternative communication channels and information sources between various geographical regions that differ in resource availability, disaster characteristics and information availability, which becomes more important when recognizing the location or place-based efficacy of alternative information sources on disaster preparedness and response. Despite millions of dollars being spent by various disaster management organization's on educating the public on disaster preparedness, this education and information only reaches a small portion of the population in the U.S (Rivera 2021). Better understanding the roles of information sources and the flow of disaster preparedness information across different geographical regions is important, as information, education and outreach related to wildfires may have more impact if it moves along information pathways that influence wildfire perceptions that promote more impactful mitigation, preparedness, and response (Comfort et al. 2004). Currently, the influence of these information pathways is not as well understood in the Great Plains of the U.S. as in other regions of the country, which have received more attention (Gafford 2024).

The purpose of this study is to examine the influence of alternative information sources on the level and perception of wildfire and disaster preparedness of households across states in the

western U.S in a wildfire context. Specifically, we examine how different information sources (e.g. internet, television/radio, public announcements, etc.) influence households' perceived level of wildfire and overall disaster preparedness and the perceived confidence level to prepare for a wildfire or such disaster across states in the GP compared to those in the more MW using three years of primary survey data collected by the U.S. Federal Emergency Management Agency (FEMA) National Household Survey that targeted areas that face an increased risk of wildfires in the year surveyed.²³

Primary findings show that information flows about disaster preparedness information and events differ between the GP and MW in the U.S. For households in the GP, the perceived level of disaster preparedness was influenced by information flow through the networks and the internet. In contrast, in the MW, the perceived level of disaster preparedness was influenced by all sources of information, except television and radio. Generally, the perceived confidence level to prepare for a disaster was primarily influenced by information flows from television/radio, public announcements, the internet, and networks. However, for the perceived confidence level to prepare for wildfire, only the internet and networks significantly influenced the perceived level of confidence.

This study contributes to the literature by highlighting the influence of alternative information sources on households' perceived level of wildfire and overall disaster preparedness across states in the GP of the U.S., which has not been extensively studied and does not have access to the same level of resources as states in the MW of the U.S. Understanding these differences can help reach vulnerable and at-risk populations during a wildfire event, especially in more rural areas. The study

²³ Perceived confidence level to prepare for a disaster captures the area-specific disaster.

provides evidence about the influence of information sources on promoting disaster preparedness, which can positively influence wildfire response in both the GP and MW of the U.S. Information can be used to better target, improve effectiveness, and enhance the distribution of resources to provide critical information about wildfire preparedness and events that reduce wildfire household impacts in the future.

2. Methods

2.1 Hypotheses

Our study assumes that households' wildfire and disaster preparedness – the ability to plan for, mitigate, and respond to wildfire risks and events – is crucial for effective wildfire management, response, and mitigation of impacts at the household level, as supported by the literature. Our focus in this study is on how disaster and wildfire preparedness are influenced by region-specific sources of information on disaster preparedness and risk. In addition, we examine how geography, prior wildfire experience, perceived likelihood of a wildfire event and demographic characteristics influence and predict household disaster preparedness.

Our conceptual framework for this study is provided in Figure 3.1. We model a household's wildfire and disaster preparedness using two measures: (1) a household's perceived wildfire and overall disaster preparedness level and (2) a household's confidence that they can be prepared for a wildfire or disaster event. The first measure captures a household's preparedness for a wildfire and is more directly connected with adoption of actual preparedness and mitigation practices, as well as associated behavioral responses (e.g. willingness to evacuate) (Brown et al., 2021; Brown et al., 2024; DeBastaini et al., 2014). The second measure is related but is used to capture a household's behavioral intention for getting prepared for wildfire or disaster risks and events.

Bergtold et al. (2024) found that agricultural producers in the Southern Great Plains of the U.S. may not adopt wildfire mitigation and preparedness practices because they believe their efforts will not be effective. Similar findings have been found for forest landowners in the U.S., as well (Gan et al., 2015). This ability to prepare is related to a household's or person's locus of control or belief that they can control outcomes in their lives, which has been shown to be an influential social-psychological behavioral factor in being prepared for natural disasters (Antwi-Boasiako, 2017; Najafi et al., 2017). For example, if a household perceives wildfire as intrinsically uncontrollable and the level of damage is random, the household will not likely invest in wildfire mitigation (Winter and Fried 2000). However, if a household perceives wildfire as a part of life and, at some level, it can be controlled, then they are more likely to be prepared for a wildfire event (Tara K. McGee and Russell 2003). We assume the perceived confidence level to prepare for a wildfire and disaster is also co-determined by the perceived likelihood of a wildfire event occurring. Literature shows that the perceived likelihood of a wildfire occurring, an aspect of wildfire risk for a household, can significantly influence wildfire preparedness and is shaped by how someone perceives preparedness (McNeill et al., 2013; Martin et al., 2007).

Figure 3.1 illustrates the hypothesized relationships between information sources and geography (region) to a household's perceived level of wildfire and disaster preparedness and perceived confidence level to prepare for a wildfire or disaster. Wildfire and disaster perceptions depend on whether a household receives any kind of wildfire information (Brenkert-Smith et al. 2012). Specialized wildfire information can enhance wildfire mitigation strategies (Brenkert-Smith et al. 2012). We include and test alternative information channels or sources of obtaining disaster preparedness information to investigate whether a household's perceived level of wildfire and disaster preparedness and the perceived confidence level to prepare for a wildfire or disaster

depend on the information channel used to provide disaster preparedness information. Tested hypotheses are based upon literature and are summarized in Table 3.1. Hypotheses H_{1a} to H_{1e} examine the hypothesized effect of alternative information sources on the perceived level of wildfire (disaster) preparedness, while hypotheses H_{2a} to H_{2e} examine the hypothesized effect of information sources on the perceived confidence level to prepare for a wildfire or disaster. As seen in Table 3.1, we test each hypothesis to examine the influence of an information source on study outcomes and then examine if there are differences between the two geographic regions in the study. We expect the influence of different information sources to be significant and to vary across regions.

Figure 3.1. Conceptual Framework of How Alternative Information Sources, Region, Prior Wildfire Experience, and Demographic Factors Influence the Perceived Level of Wildfire and Disaster Preparedness and the Perceived Confidence Level to Prepare for a Wildfire or Disaster. Solid Lines Indicate Hypothetical Relationships of Interest for This Study, With Hypothesis Numbers Indicated. Dotted Lines Represent Other Controlling Factors That Can Influence the Perceived Level of Wildfire and Disaster Preparedness and the Perceived Confidence Level to Prepare for a Wildfire or Disaster

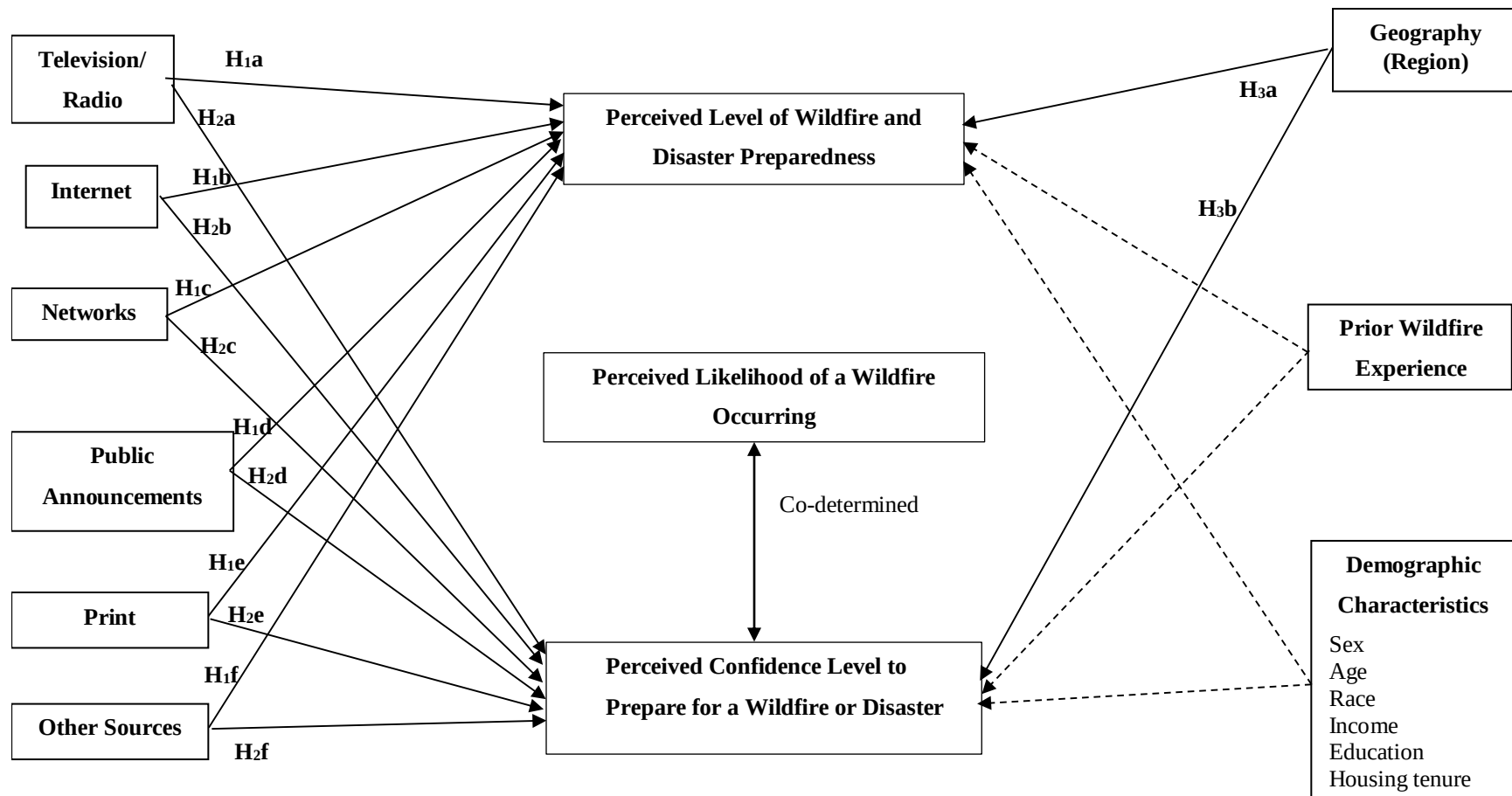


Table 3.1. Hypothesized Relationships Between Alternative Information Channels and Sources and Geographic Region on Households' Perceived Level of Wildfire and Disaster Preparedness and Perceived Confidence Level to Prepare for a Wildfire or Disaster

Hypothesis	Description
H _{1a_1}	Television/radio positively influences households' perceived level of wildfire (or disaster) preparedness.
H _{1a_2}	The influence of television/radio is greater in the MW than in the GP on the perceived level of wildfire and disaster preparedness.
H _{1b_1}	The internet positively influences the perceived level of wildfire and disaster preparedness.
H _{1b_2}	The influence of the internet is greater in MW than in the GP on the perceived level of wildfire and disaster preparedness.
H _{1c_1}	Networks positively influence the perceived level of wildfire and disaster preparedness.
H _{1c_2}	The influence of networks is greater in the MW than in the GP on the perceived level of wildfire and disaster preparedness.
H _{1d_1}	Public announcements positively influence the perceived level of wildfire and disaster preparedness.
H _{1d_2}	The influence of public announcements is greater in MW than in the GP on the perceived level of wildfire and disaster preparedness.
H _{1e_1}	Print positively influences the perceived level of wildfire and disaster preparedness.
H _{2e_2}	The influence of print is greater in the MW than in the GP on the perceived level of wildfire and disaster preparedness.
H _{1f_1}	Other sources positively influence the perceived level of wildfire and disaster preparedness.
H _{1f_2}	The influence of other sources is greater in MW than in the GP on the perceived level of wildfire and disaster preparedness.
H _{2a_1}	Television/radio positively influences the perceived confidence level to prepare for a wildfire or disaster.
H _{2a_2}	The influence of television/radio is greater in MW than in the GP on the perceived confidence level to prepare for a wildfire or disaster.
H _{2b_1}	The internet positively influences the perceived confidence level to prepare for a wildfire or disaster.
H _{2b_2}	The influence of the internet is greater in MW than in the GP on the perceived confidence level to prepare for a wildfire or disaster.
H _{2c_1}	Networks positively influence the perceived confidence level to prepare for a wildfire or disaster.
H _{2c_2}	The influence of networks is greater in the MW than in the GP on the perceived confidence level to prepare for a wildfire or disaster.
H _{2d_1}	Public announcements positively influence the perceived confidence level to prepare for a wildfire or disaster.
H _{2d_2}	The influence of public announcements is greater in MW than in the GP on the perceived confidence level to prepare for a wildfire or disaster.
H _{2e_1}	Prints positively influence the perceived confidence level to prepare for a wildfire or disaster.

H _{2e_2}	The influence of prints is greater in the MW than in the GP on the perceived confidence level to prepare for a wildfire or disaster.
H _{2f_1}	Other sources influence the perceived confidence level to prepare for a wildfire or disaster.
H _{2f_2}	The influence of other sources is greater in MW than in the GP on the perceived confidence level to prepare for a wildfire or disaster.
H _{3a}	The perceived level of wildfire and disaster preparedness is greater overall in the MW compared to the GP.
H _{3b}	The perceived confidence level to prepare for a wildfire or disaster is greater overall in the MW compared to the GP.

Note: GP represents the Great Plains states in the U.S. MW represents the mountainous western states in the U.S.

Assuming the same wildfire adaptive capacity across regions and communities would be misleading; therefore, we included region as a tested hypothesis and one of the factors that influences the perceived level of wildfire and disaster preparedness (H_{3a}) and the perceived confidence level to prepare for a wildfire or disaster (H_{3b}). A community with a higher adaptive capacity is less vulnerable during a wildfire and recovers more quickly in the aftermath of a disaster (Kolden and Henson 2019). Paveglio, Abrams and Ellison (2016) found that a person's perceptions and actions on wildfire management are influenced by the local context, such as the history and relationship between the residents and the landscape. Thus, two areas can have different views on how effective a mitigation strategy is in protecting property and life (Lindell and Prater 2002, 2000). We expect differences over space (i.e., across regions) with respect to the influence of geography on the perceived level of disaster preparedness and the perceived confidence level to prepare for a disaster.

In our study, we control for prior wildfire experience, given our wildfire context, because experiencing repeated and recent wildfires may increase the likelihood of being prepared and the confidence level in being prepared (Adhikari et al. 2023; Paveglio et al. 2015; Wilson et al. 2011). Confidence levels can be adversely impacted, though, if a household has experienced a significant loss of property due to wildfires (Winter and Fried 2000; Tara K. McGee et al. 2009; Tara K.

McGee and Russell 2003). For example, Winter and Fried (2000) found that households that have had their property destroyed perceive wildfire to be more uncontrollable compared to seasonal and permanent residents who have never experienced such a loss. In contrast, Wilson et al. (2011) found that households that had prior wildfire experience were relatively or extremely confident that wildfire management decisions were sound. Wildfire experience can shape how individuals behave when considering adoption of wildfire and disaster preparedness and mitigation practices (S. K. Jacobson et al. 2001; Jarrett et al. 2009; T.K. McGee 2011; Paveglio et al. 2015). Thus, the type of experience with wildfires can result in both an increase and a decrease in the perceived level of wildfire and disaster preparedness and the perceived confidence level to prepare for a wildfire or disaster.

Lastly, we included demographic variables as controls. Previous studies have provided evidence that it may be difficult to predict the effect or influence of demographics on individuals' actions after a disaster (Wong et al. 2023; Lindell et al. 2018). We do not have any specific expectations on the direction of influence of alternative demographic factors but recognize that they can play an important role in shaping wildfire and disaster preparedness, confidence in being prepared, and perceived likelihood of a wildfire occurring. Demographic variables included in our study include age, gender, monthly income, race, education, and housing tenure. Housing tenure or patterns of seasonal occupancy may not influence wildfire risk reduction policy actions (Muller and Schulte 2011). Higher education levels may influence the adoption of wildfire and disaster mitigation practices (Richmond 2021; Muller and Schulte 2011) and whether an individual will seek out disaster preparedness information (Rivera 2021). Hazard adaptive capacity depends on financial capacity (Lindell and Prater 2000), so that high-income households may be less affected by wildfires (Kolden and Henson 2019). Race can also influence the level of preparedness and

affect the type of disaster preparedness information an individual may seek (Rivera 2021; Rao et al. 2022).

2.2 Empirical Methods

We adopt two regression frameworks, a bivariate probit model and an ordered probit model, to test our hypotheses and assess the influence of alternative information sources and geography on the perceived level of wildfire and disaster preparedness and the perceived confidence level to prepare for a wildfire or disaster, while controlling for prior wildfire experience and demographic factors. Previous studies have directly associated the perceived confidence level to prepare for a disaster directly to disaster preparedness (Rao et al. 2022; Adame and Miller 2014). It is likely that the perceived level of wildfire and disaster preparedness and the perceived confidence level to prepare for a wildfire or disaster are co-determined. Being well prepared involves both practical and mental preparedness measures (Eriksen and Prior 2013), and adopting wildfire mitigation measures reinforces a person's confidence in their ability to respond to a wildfire (Tara K. McGee and Russell 2003). In this study, though, we do not directly model perceived confidence level to prepare for a wildfire or disaster as a factor that directly determines the perceived level of wildfire and disaster preparedness. Due to data limitations, we were unable to determine or find unique independent factors that would influence one of the factors and not the other (i.e. strong instruments) that would allow us to control for this endogeneity in our empirical approach. Thus, we consider two models, adopting a reduced form approach for our analysis. Wildfires have exhibited changes over time, as well. Taking this into consideration, we include time or temporal fixed effects as another explanatory element in our empirical framework since wildfire response or choices depend on wildfire characteristics, which have changed over time (Wong et al., 2023).

2.2.1 Ordered Probit Model to Determine Factors Driving the Perceived Level of Wildfire and Disaster Preparedness

We used a standard ordered probit model because of the ordinal nature of the two dependent variables capturing the perceived level of wildfire and overall disaster preparedness (Table 3.2). Perceived level of wildfire preparedness is wildfire specific and perceived level of disaster preparedness is overall disaster preparedness, which still would influence being prepared for a wildfire, as it includes some measures such as setting up food and water supplies and evacuation routes among others that cut across various disasters. These categories included: not prepared and do not intend to prepare in the next year (0, base), not prepared but intend to start preparing in the next year (1), not prepared but intend to get prepared in the next six months (2), have been prepared for the last year (3), and have been prepared for more than a year and continuing to prepare (4). We follow the specification for the ordered probit model in Greene (2018). We specified the index function or predictor of the ordered probit model, assuming linearity in the parameters. We included temporal fixed effects for two of the three survey years, a geography dummy for households in MW, and interaction terms between MW and the temporal fixed effects and information sources. The predictor for the two ordered probit models is specified as:

$$(1) \eta(x) = \beta_0 + \beta_1 GP + \beta_2 2018 + \beta_3 2019 + \beta_4 GP * 2018 + \beta_5 GP * 2019 + \beta_6 Television/radio + \beta_7 Television/radio * GP + \beta_8 internet + \beta_9 internet * GP + \beta_{10} network + \beta_{11} network * GP + \beta_{12} public + \beta_{13} public * GP + \beta_{14} print + \beta_{15} print * GP + \beta_{16} Other Sources + \beta_{17} Other Sources * GP + \beta_{18} exp + \beta_{19} exp * GP + \beta_{20} age + \beta_{21} fem + \beta_{22} own + \beta_{23} other + \beta_{24} educ + \beta_{25} moine + \beta_{26} white$$

Definitions and descriptions of the independent variables are provided in Table 3.3.

Table 3.2. Description and Summary of Dependent Variables for All Respondents, Respondents Broken out by Region (GP Versus MW), and P-Values for a Two-Sample T-Test Between the Two Regions

Variable	Description	All respondents		Great Plains (GP) respondents		Western States (MW) respondents		Two-Sample T-test P-Values
		N	%	N	%	N	%	
Binary Dependent Variables								
Perceived wildfire occurrence	=1 if it is likely that a wildfire could happen in the area, 0 otherwise	836	57.5%	129	53.5%	707	58.3%	0.31
Adoption of Defensible space	=1 if the household has adopted defensible space against a wildfire, 0 otherwise	823	66.5%	127	63.0%	696	67.1%	0.37
Perceived confidence in being prepared for a disaster	=1 if the household has a high perceived confidence level to prepare for a disaster (extremely confident) ^a , 0 otherwise	836	38.9%	129	40.3%	707	38.6%	0.72
Perceived confidence in being prepared for a wildfire	=1 if the household has a high perceived confidence level to prepare for wildfire (extremely confident) ^a , 0 otherwise	487	43.3%	121	43.0%	366	43.4%	0.93
Categorical Dependent Variable								
Perceived level of disaster preparedness Level								
0	If the household is not prepared, and they do not intend to prepare in the next year	70	8.3%	13	10.1%	57	8.1%	0.26
1	If the household is not prepared but intends to start preparing in the next year	88	10.5%	13	10.1%	75	10.6%	
2	If the household is not prepared but intends to get prepared in the next six months	155	18.5%	17	13.2%	138	19.5%	
3	If the household has been prepared for the last year	139	16.6%	28	21.7%	111	15.7%	
4	If the household has been prepared for more than a year and continues preparing	384	45.9%	58	45.0%	326	46.1%	

Variable	Description	All respondents		Great Plains (GP) respondents		Western States (MW) respondents		Two-Sample T-test P-Values
		N	%	N	%	N	%	
Perceived level of wildfire preparedness Level								
0	If the household is not prepared, and they do not intend to prepare in the next year	31	8.8%	2	7.4%	29	8.9%	0.88
1	If the household is not prepared but intends to start preparing in the next year	36	10.2%	3	11.1%	33	10.1%	
2	If the household is not prepared but intends to get prepared in the next six months	72	20.4%	7	25.9%	65	19.9%	
3	If the household has been prepared for the last year	54	15.3%	5	18.5%	49	15.0%	
4	If the household has been prepared for more than a year and continues preparing	160	45.3%	10	37.0%	150	46.0%	

^a A household has a high perceived confidence level to prepare for a wildfire or disaster if they are extremely confident they can take steps to prepare for a wildfire or disaster.

Table 3.3. Description and Summary of Independent Variables for All Respondents, Respondents Broken out by Region (GP Versus MW), and P-Values for a Two-Sample T-Test between the Two Regions

Variable	Description	Census (Study Region) ^a	All respondents		Great Plains (GP) respondents		Western States (MW) respondents		Two-Sa mple T- test P- Values
			N	%	N	%	N	%	
None (Base)	=1 if no information, 0 otherwise		836	30.6%	129	48.1%	707	27.4%	<0.00
Television/ Radio	=1 if the information is from TV, TV News, weather channels, and commercials on TV/Radio, 0 otherwise		836	40.6%	129	31.0%	707	42.3%	0.02
Internet	=1 if the information is from the internet and social media, 0 otherwise		836	22.9%	129	14.7%	707	24.3%	0.02
Networks	=1 if the information is from conversations with others, provided by the employer at work, and events/training, 0 otherwise		836	9.2%	129	7.0%	707	9.6%	0.34
Public	=1 if the information is from public service announcements, notices from the local government or community, and utility/local businesses, 0 otherwise		836	7.7%	129	4.7%	707	8.2%	0.16
Print	=1 if the information is from newspapers, brochures, pamphlets, and flyers, 0 otherwise		836	13.9%	129	7.8%	707	15.0%	0.03
Other Sources ^b	=1 if the information is from other sources, 0 otherwise		836	10.4%	129	3.1%	707	11.7%	0.00
Educ	=1 if the household is a college graduate, 0 otherwise	-	836	71.7%	129	69.8%	707	72.0%	0.61
Fem	=1 if the respondent is female, 0 otherwise	50.2	836	46.2%	129	48.8%	707	45.7%	0.51
Exp	=1 If a household ever experienced a wildfire or natural wildfire	-	836	36.1%	129	32.6%	707	36.8%	0.36

White	=1 if the respondent is white, 0 otherwise	70.6	836	76.1%	129	78.3%	707	75.7%	0.52
GP	=1 if the household is in GP, 0 if in MW	-	836	84.6%					
2018	=1 if year is 2018, 0 otherwise		836	29.9%	129	51.2%	707	26.0%	<0.00
2019	=1 if year is 2019, 0 otherwise		836	29.3%	129	45.0%	707	26.5%	<0.00
2020 (Base)	=1 if year is 2020, 0 otherwise		836	40.8%	129	3.9%	707	47.5%	<0.00
Own	= 1 if household owns the home, 0 otherwise		836	68.4%	129	75.2%	707	67.2%	0.07
Other	= 1 if the household does not own or rent the home, 0 otherwise		836	2.6%	129	1.6%	707	2.8%	0.40
Rent (Base)	= 1 if the household rents the home, 0 otherwise		836	29.0%	129	23.3%	707	30.0%	0.12
		Mean	N	Mean (Standard Deviation)	N	Mean (Standard Deviation)	N	Mean (Standard Deviation)	
Moinc	Monthly household income (\$)	7941	836	13104 (21117)	129	12751 (21165)	707	13168 (21123)	0.84
Age	Respondent age in years	Median 36.7	N 836	Median 54	N 129	Median 54	N 707	Median 54	0.86

^a Population estimates for Census data were obtained from <https://www2.census.gov/programs-surveys/popest/datasets/> and gender, age, race, and monthly income were obtained from <https://data.census.gov>.

^b Other sources of information include mail, email, magazines, billboards, FEMA, and reverse 911, among others.

While the signs of the coefficients in the ordered probit model indicate directions of change (i.e. a positive sign indicates a factor has a positive influence on a household having a high perceived level of wildfire or disaster preparedness), they provide little information about the magnitude of the influence of the explanatory variable on the probability of being at a given level of preparedness. Thus, we estimate marginal effects for each explanatory variable in the model following Greene (2018) for each category (level) of the dependent variable when GP, a binary variable indicating a survey respondent lives in the Great Plains, is equal to one and when GP is equal to zero. This is done in order to capture the marginal effects of information sources and other factors on wildfire and disaster preparedness in the GP and MW, separately. The marginal effects provide substantive information about the marginal change in the probability of being in a particular ordinal preparedness category (level of preparedness) given a one-unit change in an explanatory variable. For binary independent variables, this is calculated as a discrete difference. Marginal effects are estimated as partial averages across respondents, and asymptotic standard errors are estimated using the delta method (Greene, 2018). It is the significance of these marginal effects that is used to examine hypotheses H_{1a_1}, H_{1b_1}, H_{1c_1}, H_{1d_1}, H_{1e_1}, and H_{1f_1}. The hypotheses H_{1a_2}, H_{1b_2}, H_{1c_2}, H_{1d_2}, H_{1e_2}, and H_{1f_2} are tested using the associated marginal effects for models estimated for each region separately and the statistical significance of the interaction terms in equation (1).

2.2.2 Probit Model to Determine Factors Driving the Adoption of Defensible Space

We used a probit model to better understand the effect of information sources on the adoption of a specific wildfire preparedness practice, i.e. creating a defensible space. A defensible space is an area surrounding a structure where vegetation has been cleared or changed as a wildfire management practice, and it is among the effective strategies used to prevent wildfire damage to

structures (Syphard et al. 2014; J. D. Cohen 2000). The dependent variable, the adoption of defensible space, is a binary outcome, as shown in Table 3.2, and the same set of independent variables as specified in equation (1) is used to estimate the probit model. We assume a linear relationship between the dependent and the independent variables, and that the error term follows a normal distribution. We use maximum likelihood estimation to estimate the Probit model. We use the coefficient of the probit model to show the direction of change for each of the explanatory variables and compute average marginal effects across respondents for each region (MW and GP) to capture the magnitude of change. The asymptotic standard errors are estimated using the delta method (Greene, 2018).

2.2.3 Bivariate Probit Model Examining the Influence of Factors on the Perceived

Likelihood of a Wildfire Event Occurring and the Perceived Confidence Level to Prepare for a Wildfire or Disaster

A bivariate probit model is utilized when two binary dependent variables are co-determined (Greene 2018; Monfardini and Radice 2008). In this study, we use the bivariate probit model to capture the relationship (correlation) between the perceived likelihood of a wildfire event occurring (y_1) and the perceived confidence level to prepare for a wildfire or disaster. We represent the perceived confidence level to prepare for a disaster as y_2 and the perceived confidence level to prepare for a wildfire as y_3 .²⁴ y_2 is a general question on disaster confidence, but focuses on a wildfire context, as data was targeted specifically to areas with high wildfire risk. The bivariate

²⁴We also speculated that perceived confidence level to prepare for a disaster and perceived level of disaster preparedness are also co-determined and estimated a bivariate probit model with the two binary dependent variables. However, we did not have enough variability in the data for the GP, and the model did not converge. Therefore, we estimated an ordered probit model to determine what factors drive the perceived level of disaster preparedness.

model is used to estimate the influence of the factors highlighted in Figure 3.1 on the perceived likelihood of a wildfire event occurring and perceived confidence level to prepare for a wildfire or disaster, while accounting for the dependence between the two dependent outcomes. The bivariate probit model adopted here follows standard specification and is a reduced form model (Greene, 1996; Ramsey et al., 2019; Greene, 2018; Gkritza, 2009; Russo et al., 2014; and Seyoum, 2018). We assume that underlying each observed endogenous variable (y_1 and y_2) and (y_1 and y_3) is a latent process that is a function of the set of factors shown in Figure 3.1 and an additive mean-zero IID error term. The error terms for each of the processes are assumed to be correlated. The researcher only observes a binary outcome, though, for each latent process (e.g. the choice). Mathematically, for (y_1 and y_2), we are looking at how wildfire risk influences overall the perceived confidence level to prepare for a disaster in an area with high wildfire risk (i.e. in a wildfire context), and we have:

$$(2) \quad y_1^* = \mathbf{x}_1' \boldsymbol{\beta}_1 + \varepsilon_1, \quad y_1 = 1 \text{ if } (y_1^* > 0)$$

$$(3) \quad y_2^* = \mathbf{x}_2' \boldsymbol{\beta}_2 + \varepsilon_2, \quad y_2 = 1 \text{ if } (y_2^* > 0)$$

$$(4) \quad \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} | \mathbf{x}_1, \mathbf{x}_2 \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right]$$

where y_1^* and y_2^* are latent dependent variables (our outcomes), $\mathbf{x}_1$ and $\mathbf{x}_2$ are vectors representing explanatory variables that influence each latent process (following Figure 3.1), $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are vectors of parameters, ε_1 and ε_2 are mean zero IID disturbance terms, and ρ is the correlation coefficient between ε_1 and ε_2 . For y_1 and y_3 , the mathematical equations are like those stated above, replacing y_2 with y_3 . For this model, we are interested in how wildfire risk influences the perceived confidence level to prepare for a wildfire in an area with high wildfire risk and in a wildfire context as well. Following convention, we assumed the relationship between the dependent and independent variables is linear for each latent process, following a specification

similar to equation (1). Thus, the explanatory factors include those presented in Figure 3.1 and defined in Table 3.3. As in equation (1), interaction terms between area and year, area and experience with wildfire, and area and information source to capture differences between the two regions (the mountainous western regions (MW) and the Great Plains (GP)) are included.

Using probabilistic mathematics to examine the four outcomes from the two binary dependent variables, the probabilities of the different outcomes for the two dependent variables (y_1 and y_2) are:

$$\begin{aligned}
 (5) \quad & P(y_1 = 1, y_2 = 1 | \mathbf{x}_1, \mathbf{x}_2) = P_1 = \Phi_2(\mathbf{w}_1, \mathbf{w}_2, \rho^*) \\
 & P(y_1 = 1, y_2 = 0 | \mathbf{x}_1, \mathbf{x}_2) = P_2 = \Phi(\mathbf{x}_1' \boldsymbol{\beta}_1) - P(y_1 = 1, y_2 = 1 | \mathbf{x}_1, \mathbf{x}_2) \\
 & P(y_1 = 0, y_2 = 1 | \mathbf{x}_1, \mathbf{x}_2) = P_3 = \Phi(\mathbf{x}_2' \boldsymbol{\beta}_2) - P(y_1 = 1, y_2 = 1 | \mathbf{x}_1, \mathbf{x}_2) \\
 & P(y_1 = 0, y_2 = 0 | \mathbf{x}_1, \mathbf{x}_2) = P_4 = 1 - P_1 - P_2 - P_3
 \end{aligned}$$

where, the individual subscript is suppressed for convenience, Φ_2 and Φ represent the bivariate and univariate standard normal CDFs, $\mathbf{w}_j = q_j \mathbf{x}_j' \boldsymbol{\beta}_j$, $\rho^* = q_1 q_2 \rho$ for $j = 1, 2$, and $q_j = 2y_j - 1$, where $q_j = 1$ if $y_j = 1$ and -1 if $y_j = 0$ for $j = 1, 2$ (Gourieroux 2000; Greene 2018). The model is estimated using the method of maximum likelihood (see Greene, 2018). The four probabilities for y_1 and y_3 for the other bivariate model follow the same specification as equation (5) by replacing y_2 with y_3 .

The coefficients from the bivariate probit model can be difficult to explain because the coefficient enters the probability for all the outcomes in the model. A better estimate for inferential purposes is the marginal effect estimates, which allow for clearer assessments of the direction and magnitude of change in the probability of outcomes for different explanatory factors (Russo et al. 2014). The marginal effects of changes in covariates on the probability of a given set of outcomes is given by:

$$(6) \quad \frac{dP_1}{dx_i} = \frac{d\Phi_2(\mathbf{x}_1' \boldsymbol{\beta}_1, \mathbf{x}_2' \boldsymbol{\beta}_2, \rho)}{dx_i} = \phi(\mathbf{x}_i' \boldsymbol{\beta}_i) \Phi \left[\frac{[\mathbf{x}_2' \boldsymbol{\beta}_2 - \rho^* \mathbf{x}_1' \boldsymbol{\beta}_1]}{\sqrt{1 - \rho^{*2}}} \right] \beta_i, i = 1, 2$$

$$\begin{aligned}\frac{dP_2}{dx_i} &= \frac{d\Phi(x_1'\beta_1)}{dx_i} - \frac{dP_1}{dx_i}, i = 1,2 \\ \frac{dP_3}{dx_i} &= \frac{d\Phi(x_2'\beta_2)}{dx_i} - \frac{dP_1}{dx_i}, i = 1,2 \\ \frac{dP_4}{dx_i} &= -\frac{dP_1}{dx_i} - \frac{dP_2}{dx_i} - \frac{dP_3}{dx_i}, i = 1,2\end{aligned}$$

where ϕ denotes the univariate standard normal density. The derivative $\frac{d\Phi(x_j'\beta_j)}{dx_i}$ for $j = 1,2$ are marginal effects for the associated univariate probit models for a given explanatory factor x_i when $y_j = 1$. The marginal effects here represent marginal changes in the bivariate probability of a given set of outcomes, such as perceiving a wildfire is likely to occur ($y_1 = 1$) and a high perceived confidence level in being prepared for disaster ($y_2 = 1$) or having a high perceived confidence level in being prepared for wildfire ($y_3 = 1$), given a one unit change in an explanatory variable or factor. For binary dependent variables, this is calculated as a discrete difference. All marginal effects are estimated as partial averages across respondents, and standard errors are estimated using the delta method (Gourieroux, 2000; Greene, 2018). We utilize the significance of the coefficients to test the hypotheses H2a_1, H2b_1, H2c_1, H2d_1, H2e_1, and H2f_1. The hypotheses H2a_2, H2b_2, H2c_2, H2d_2, H2e_2, and H2f_2 are tested using the statistical significance of the interaction terms in the bivariate probit model and the associated marginal effects for models estimated for each region separately.

3. Study Region and Data

3.1 Study Region

This study looks at and compares two fire-prone regions of the U.S. (See Figure 3.2) The Mountainous western states (MW) and the states across the Great Plains (GP). The states covered

in the study are shown in Figure 3.2. The states in the GP are MN, SD, NE, KS, MO, OK, AR, and TX, while those in the MW are WA, MT, OR, ID, WY, CA, NV, UT, CO, AZ, and NM.

Figure 3.2. Map Showing the Great Plains (GP) and Mountainous West States (MW) in the Study Region, With the Number of Observations in Each State



The MW are characterized by heterogeneous vegetation ranging from lower-elevation grasslands, shrub lands, and forest ecotones to continuous montane and subalpine forests and, in some cases, alpine tundra (Littell et al. 2009). MW are more susceptible to unpredictable wildfires because of its atmospheric environment (Luo et al. 2013). The Northern Rockies forest recorded the highest numbers of wildfires in the western states and accounted for a 50% increase in large wildfires (A. L. Westerling et al. 2006; Anthony LeRoy Westerling 2016). A study by Westerling

(2016), covering a period from 1973 to 2012, found that western US forests observed more than a 140% average annual increase in wildfires in the subsequent decades (1984 to 2012) compared to the first decade (1973 to 1983). Data also shows that compared to the first decade (1973 to 1983), annual area burned by wildfire has increased by 390% on average for the subsequent decades (1984 to 2012). This is equivalent to a 123,000-ha increase in burned areas per decade. Similar trends were also observed in non-forest vegetation areas, where wildfire frequency increased, and the area burned increased by 40,585 ha per decade (Anthony LeRoy Westerling 2016).

The GP of the U.S., which was once characterized by native grasslands and wetlands, has changed over time to a mosaic of rangeland, dryland farming, and intensive irrigated and industrial agriculture (Sohl et al. 2012; Drummond et al. 2012). The GP faces an increased incidence and risk from wildfires, with more than half of the ecoregions in this region having a greater than 70% chance of a large wildfire occurring (V. M. Donovan et al. 2017). These ecoregions have experienced an increased number of large wildfires, increased area burned by wildfires, and/or a significantly increased likelihood of a wildfire event occurring in the near future (V. M. Donovan et al. 2017). Predictions for the GP show that the South-Central US will face the greatest impact from enhanced wildfire risk due to climate change compared to the Western or Southwestern US (An, Gan, and Cho, 2015), with the greatest impact in the southwestern GP (Fang et al. 2025).

3.2 Data

This study uses 3 years of the annual national household survey covering the years 2018 to 2020, conducted by the Federal Emergency Management Agency (FEMA) (FEMA and National Household Survey 2025). The annual national household survey is a nationally representative sample that examines levels of disaster preparedness, disaster risk perceptions, mitigation and

adaptation actions, and motivations for disaster preparedness.²⁵ FEMA conducted cross-sectional annual telephone surveys between 2013 and 2023, randomly selecting respondents from both landlines and cell phone numbers in an area within the country that has a high risk of having one of the 6 hazards surveyed about during the years of the survey examined: floods, hurricanes, tornadoes, wildfires, earthquakes, and a nuclear explosion. Each hazard that is interviewed by FEMA is referred to as a hazard-specific oversample.²⁶ We specifically assess responses from the wildfire oversamples for the 2018 to 2020 annual surveys. This allows us to focus on households that are in an area that is prone to high wildfire risk, providing our wildfire context for the study (FEMA, and National Household Survey 2018). That is, our study examines wildfire and disaster preparedness and confidence in being prepared within a wildfire context based on local areas that exhibit increased wildfire risk.

Sample sizes ranged between 500 and 515 for each of the three years examined in this study (FEMA, and National Household Survey 2018; FEMA 2019, 2020). In total, we had 1,529 observations. We then restricted the sample to only respondents who were located in the MW and the GP, reducing our total sample by 294 observations. We examine the perceived level of wildfire and overall disaster preparedness given their high correlation to each other, as well as confidence in being prepared for a wildfire or disaster among households across different states within our study region in a wildfire context. The overall dataset contained 836 observations with more than two hundred households per year. We dropped observations with missing values for the factors

²⁵ This dataset can be found at <https://www.datalumos.org/datalumos/project/218642/version/V1/view>. (Federal Emergency Management Agency (FEMA), 2025)

²⁶ While the household survey data was collected by FEMA, we did obtain IRB approval for the study (IRB Proposal IRB-10721, Kansas State University)

modeled in the study.²⁷ The year 2020 contains about 40% of the observations, with the other 2 years constituting around 60% of the sample. Most observations (48%) were captured in 2020 for MW and in 2018 and 2019 for the GP. The differences in the number of observations by year and region are due to increased projection of major wildfire events, which determine where the survey was administered (FEMA, 2025).

The dependent variables of interest are the perceived level of disaster preparedness and the perceived confidence level to prepare for a disaster. The question on the survey: *“Thinking about preparing yourself for a disaster, have you developed and discussed an action plan with your family, that includes information about how to leave your community or where to shelter, and have set aside supplies such as food, water, and other essentials that allow you to be self-sufficient for at least three days? Which of the following best represents your preparedness?”* was used to capture the perceived level of disaster preparedness (FEMA and National Household Survey 2025). The coded levels for this question are provided in Table 3.2. The question on the surveys asking: *“How confident are you that you can take the steps to prepare for a disaster in your area?”* was utilized to capture the perceived confidence level to prepare for a disaster (FEMA and National Household Survey 2025). This variable had 5 levels (not at all confident, slightly confident, somewhat confident, moderately confident, and extremely confident), do not know, and refuse to answer as options. We recorded the question as binary, being equal to 1 if extremely confident was selected, and zero for all other levels. Respondents who refused to answer or answered do not know on any of the questions for our dependent variables (outcomes) were excluded from the data.

²⁷ We dropped 399 observations that had missing values in one or more variables.

We also conducted analysis using the perceived level of wildfire preparedness and the perceived confidence level to prepare for a wildfire. The specific survey questions were “*Thinking about preparing yourself for a wildfire, have you developed and discussed an action plan with your family that includes information about how to leave your community or where to shelter, and set aside supplies such as food, water, and other essentials that allow you to be self-sufficient for at least three days? Which of the following best represents your preparedness?*” and “*How confident are you that you can take the steps to prepare for a WILDFIRE?*” with the levels in each question highlighted in Table 3.2 (FEMA and National Household Survey 2025). We did not solely use the perceived level of wildfire preparedness as the only main dependent variable for preparedness in this study because, despite the area being classified as a wildfire-risky area, about 58% did not list wildfire events among the three top disasters with the biggest impact in the area and never answered the wildfire preparedness question.²⁸ Yet, the overall disaster preparedness should directly relate to wildfire preparedness as the survey focused on areas with high recent wildfire risk (i.e. our wildfire context). To better understand the effect of information sources on wildfire-specific preparedness, we looked at the effect of information sources on creating a defensible space. In the survey, the respondents were asked, “*Have you taken steps to protect your home from a wildfire by clearing and removing items around your house or other buildings that could easily burn*”(FEMA and National Household Survey 2025). Although the survey had a question on whether a household has a plan for where to go in case of wildfire, we do not show the results in this paper because there was not enough data for statistical model estimation; the information was missing from 44% of the sample.

²⁸ We had a total of 353 observations and only 27 observations from the GP.

Independent variables of interest include perceived likelihood of a wildfire (endogenous variable), experience with wildfire, information sources on disaster preparedness, house tenure, and demographics. The information sources on disaster preparedness were based on specific information sources or channels that households used to obtain disaster and wildfire preparedness information, which included: television/radio (TV, TV News, weather channels, and commercials on TV/Radio); internet (Internet and social media); networks (conversations with others, provided by the employer at work, and events/training); public announcement (public service announcements, notices from the local government or community, and utility/local businesses); print (newspapers, brochures, pamphlets, and flyers); and other sources (email, billboards, reverse 911, amongst other sources).²⁹ The question that captures the perceived likelihood of a wildfire event occurring was “*Thinking about the area you live in, is it likely or unlikely a wildfire could happen in your area?*” (FEMA and National Household Survey 2025). We also included fixed effects for geography with MW as the base, as well as for the year of the survey, with 2020 as the base.

The descriptive statistics for the dependent and independent variables used are provided in Tables 2 and 3, respectively. We provide the frequency in percentages for categorical variables

¹¹ The respondents were first asked, “*In the past six months, have you read, seen, or heard any information about how to get better prepared for a disaster? By disaster, I mean events that could threaten lives, disrupt public or emergency services like water and power, or damage property.*” They were then asked a follow-up question, “*How did you get the information that you read, saw, or heard about getting better prepared for a disaster?*” They were allowed to list only two sources of information. We included both in our analysis and conducted a robustness check by including only the first or primary source listed by a respondent. For wildfire, the set of questions was “*In the past six months, have you read, seen, or heard any information about how to get better prepared for a WILDFIRE?*” and “*How did you get the information that you read, saw, or heard about getting better prepared for a WILDFIRE?*”. All the survey questions were obtained from FEMA and National Household Survey (2025).

and the mean and standard deviation for continuous variables for the entire sample and for each region (i.e., MW, which represents 85% of our sample, and GP, which represents 15% of our sample). In Table 3.3, we also provide U.S. Census averages for variables when available for the entire region for the study and specific to MW and GP states (United States Census Bureau 2022). The sample is representative by gender (i.e., percent female) and race (i.e., percent white), as it is close to the U.S. Census averages; however, we observe a difference for monthly income and age. The reason for this difference likely arises due to our sample being restricted to only wildfire-specific respondents, and most of the respondents were homeowners.

Comparing census GP averages with GP-specific averages, we observe that gender and race were very close to the GP census average, while median age and monthly income differed. The 3-year (2018-2020) census averages for GP states for percent female, percent white, median age, and median monthly income were 50.4%, 74.8%, 36, and \$7,171 for each of the statistics being compared, respectively. In the MW, only gender was close to the census MW average, with race, median age, and monthly income being different. The 3-year (2018-2020) census averages for the MW states for percent female, percent white, age, and median monthly income are 50.1%, 68.1%, 37, and \$8409, respectively (U.S Census Bureau, 2022). Looking at the demographics of the respondents across both regions together, 46% of the sample were female, the average monthly income of respondents was \$13,104 (with a median income of \$5375 per month), the average median age was 54 years, 76% were whites, 72% of respondents had a college degree, 68% were homeowners, and 28% rented.

We tested for significant mean differences between levels of the dependent variables to examine hypotheses H_{3a} and H_{3b} using a Pearson two-sample mean test, and the results are discussed in Section 4.1. In addition, we examined mean differences between the independent

variables between the two regions using a two-sample t-test. For the categorical variable, the p-values are from the Pearson test, and for continuous data, the p-values are from a pooled t-test. We assume the two samples (GP and MW) are independent, and the population variances are equal. Mean differences between MW and GP were statistically significant for all of the information sources ($P < 0.10$) except for networks and public announcements (Table 3.3).

4. Results

4.1 Summary Statistics for Wildfire and Disaster Preparedness Perceptions

Wildfire was a concern for most respondents, but only 36% of households surveyed (33% in the Great Plains (GP) and 37% in the mountainous western regions (MW)) had experienced a wildfire event (Table 3.3, “exp” variable). More than 50% of the respondents perceived that a wildfire could happen in their local area in both MW and GP (Table 3.2). We did not observe any significant mean difference between household respondents in the MW and GP in perceived confidence level to prepare for a wildfire or disaster or difference in the distribution of household respondents in the MW and GP across responses to the perceived level of wildfire and disaster preparedness, indicating a lack of evidence to support hypotheses H_{3a} and H_{3b} (Table 3.2). Around 40% of household respondents in both regions had a high confidence level of being prepared for a disaster, and it was slightly higher for a high confidence level of being prepared for a wildfire. It was 43% for both the GP and the MW. Eight to ten per cent of household respondents in both regions did not perceive that they were prepared for a disaster and did not intend to take any measures with regard to disaster preparedness, but it was between 7% and 9% for wildfire preparedness. In contrast, about 45% and 46% of household respondents in the GP and MW regions, respectively, indicated they perceive themselves to be prepared for a disaster and have been so for a year or more. For the perceived level of wildfire preparedness, it was 37% in the GP and 46% in the MW.

4.2 Perceived Level of Wildfire and Disaster Preparedness and Information Flows

We estimated a series of ordered probit models, one for a perceived level of overall disaster preparedness and one for wildfire preparedness (dependent variables) following equation (1) using the same set of independent variables. The models allow us to examine general preparedness for a disaster and specific preparedness for a wildfire to test hypotheses H_{1a_2}, H_{1b_2}, H_{1c_2}, H_{1d_2}, H_{1e_2}, and H_{1f_2}.³⁰ Estimation results for the ordered probit models are reported in Table 3.4, and the corresponding marginal effects (ME) for each explanatory factor for the overall disaster preparedness level are reported in Table 3.5.³¹ Both models are in a wildfire context with interactions to capture differences between the GP and MW. Column A shows the results in Table 3.4 for Model A examining the perceived level of disaster preparedness. Column B shows the results for Model B for the ordered probit model estimated using the perceived level of wildfire preparedness.

³⁰ In the appendix in Appendix Table C.1 shows the estimation results for the ordered probit model when we only consider the primary or a single disaster preparedness information source that respondents identified that they used. We opted to generally use both information sources indicated by respondents, if provided, for a more complete assessment of the influence of information sources. Comparing results in Table 3.3 and Appendix Table C.1, the underlying findings in our study remain the same; disaster preparedness information increases the perceived level of wildfire and disaster preparedness, and the effect is region-specific.

³¹ We do not show the ME effect for the perceived level of wildfire preparedness model because the ME would not be estimated due to limited observations for the GP for the perceived level of wildfire preparedness model.

Table 3.4. Ordered Probit Estimation Results for the Perceived Level of Disaster Preparedness (Model A) and for the Perceived Level of Wildfire Preparedness (Model B)

Variables	<u>Model A</u>	<u>Model B</u>
	Perceived level of disaster preparedness	Perceived level of wildfire preparedness
GP	1.07 (0.67)	-0.20 (0.45)
2018	-0.23** (0.11)	-0.23 (0.15)
2019	-0.02 (0.11)	0.17 (0.18)
GP*2018	-0.86 (0.67)	0.77 (0.56)
GP*2019	-1.02 (0.68)	0.00 (.)
Other sources	0.25* (0.14)	0.34* (0.19)
Other sources*GP	-0.03 (0.60)	-0.23 (1.20)
Television/radio	0.11 (0.09)	0.23* (0.13)
Television/radio*GP	0.05 (0.24)	-0.09 (0.61)
Internet	0.34*** (0.10)	0.38*** (0.14)
Internet*GP	0.25 (0.33)	0.47 (0.96)
Print	0.26** (0.13)	0.39** (0.18)
Print*GP	-0.54 (0.39)	0.21 (0.91)
Public	0.92*** (0.19)	0.84*** (0.23)
Public*GP	-1.70*** (0.51)	-2.00** (0.94)
Networks	0.45*** (0.16)	0.55** (0.22)
Networks*GP	0.55 (0.49)	-0.11 (0.88)
Exp	0.25*** (0.09)	0.42*** (0.13)
Exp*GP	0.19 (0.24)	0.38 (0.53)

Age	0.01*** (0.00)	0.01** (0.00)
Fem	-0.07 (0.08)	-0.08 (0.13)
Own	0.06 (0.09)	-0.01 (0.15)
Others	-0.31 (0.24)	-0.22 (0.46)
Educ	0.19** (0.09)	-0.13 (0.15)
Moinc	0.00 (0.00)	0.00 (0.00)
White	0.07 (0.10)	0.18 (0.16)
Level (cut) 1 Threshold	-0.43*** (0.17)	-0.37 (0.27)
Level (cut) 2 Threshold	0.10 (0.16)	0.17 (0.26)
Level (cut) 3 Threshold	0.72*** (0.16)	0.87*** (0.27)
Level (cut) 4 Threshold	1.19*** (0.16)	1.31*** (0.27)
Log Likelihood	-1112.19	-463.90
Pseudo R ²	0.06	0.07
AIC	2284.38	985.80
Observations	836	353

Note: Asymptotic standard errors are in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$. Both dependent variables are ordinal variables measuring the perceived level of wildfire and disaster preparedness. Level 0 is if the household is not prepared and they do not intend to prepare in the next year. Level 1 is if the household is not prepared but intends to start preparing in the next year. Level 2 is if the household is not prepared but intends to get prepared in the next six months. Level 3 is if the household has been prepared for the last year. Level 4 is if the household has been prepared for more than a year and continues preparing.

Table 3.5. Marginal Effects for Each Explanatory Variable for Each Outcome Category for the Perceived Level of Disaster Preparedness for the Mountainous Western States (MW) and the Great Plains (GP)

Outcome Category or Level ^a	2018	2019	Other Sources	Television/radio	Internet	Print	Public	Networks	Exp	Age	Fem	Own	Other	Educ	Moinc	White
Marginal effects for ordinal categories for Model A estimated for the Great Plains (GP)																
Category 0	0.08** (0.03)	0.07*** (0.03)	-0.02 (0.04)	-0.02 (0.02)	-0.04** (0.02)	0.03 (0.05)	0.11 (0.09)	-0.05*** (0.02)	-0.04** (0.02)	-0.00*** (0.00)	0.01 (0.01)	-0.01 (0.01)	0.04 (0.03)	-0.02* (0.01)	-0.00 (0.00)	-0.01 (0.01)
Category 1	0.08** (0.03)	0.07** (0.03)	-0.02 (0.04)	-0.01 (0.02)	-0.04** (0.02)	0.02 (0.03)	0.06 (0.04)	-0.06*** (0.02)	-0.03* (0.02)	-0.00*** (0.00)	0.01 (0.01)	-0.00 (0.01)	0.02 (0.02)	-0.01* (0.01)	-0.00 (0.00)	-0.01 (0.01)
Category 2	0.12* (0.06)	0.11* (0.06)	-0.02 (0.05)	-0.02 (0.02)	-0.06* (0.03)	0.02 (0.03)	0.06** (0.03)	-0.09** (0.04)	-0.04* (0.02)	-0.00*** (0.00)	0.01 (0.01)	-0.01 (0.01)	0.03 (0.02)	-0.02* (0.01)	-0.00 (0.00)	-0.01 (0.01)
Category 3	0.07 (0.06)	0.07 (0.06)	-0.01 (0.03)	-0.01 (0.01)	-0.03 (0.02)	0.01 (0.01)	0.02 (0.01)	-0.07* (0.04)	-0.02* (0.01)	-0.00*** (0.00)	0.00 (0.00)	-0.00 (0.00)	0.01 (0.01)	-0.01** (0.00)	-0.00 (0.00)	-0.00 (0.00)
Category 4	-0.34** (0.17)	-0.33** (0.16)	0.07 (0.17)	0.05 (0.07)	0.17* (0.09)	-0.09 (0.12)	-0.24* (0.15)	0.26** (0.10)	0.13* (0.07)	0.00*** (0.00)	-0.02 (0.02)	0.02 (0.03)	-0.10 (0.08)	0.06** (0.03)	0.00 (0.00)	0.02 (0.03)
Marginal effects for ordinal categories for Model A estimated for the Mountainous Western States (MW)																
Category 0	0.04** (0.02)	0.00 (0.01)	-0.03** (0.02)	-0.02 (0.01)	0.04*** (0.01)	-0.03** (0.01)	0.08*** (0.01)	0.05*** (0.01)	0.03*** (0.01)	0.00*** (0.00)	0.01 (0.01)	-0.01 (0.01)	0.06 (0.05)	-0.03** (0.01)	-0.00 (0.00)	-0.01 (0.01)
Category 1	0.02** (0.01)	0.00 (0.01)	-0.03* (0.01)	-0.01 (0.01)	0.04*** (0.01)	-0.03** (0.01)	0.08*** (0.01)	0.04*** (0.01)	0.03*** (0.01)	0.00*** (0.00)	0.01 (0.01)	-0.01 (0.01)	0.03 (0.02)	-0.02** (0.01)	-0.00 (0.00)	-0.01 (0.01)
Category 2	0.02** (0.01)	0.00 (0.01)	-0.03* (0.02)	-0.01 (0.01)	0.04*** (0.01)	-0.03* (0.01)	0.11*** (0.02)	-0.05** (0.02)	-0.03** (0.01)	0.00*** (0.00)	0.01 (0.01)	-0.01 (0.01)	0.02* (0.01)	-0.02** (0.01)	-0.00 (0.00)	-0.01 (0.01)
Category 3	0.00 (0.00)	0.00 (0.00)	-0.01 (0.01)	-0.00 (0.00)	-0.01* (0.00)	-0.01 (0.00)	0.06*** (0.02)	-0.02 (0.01)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.01)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Category 4	-0.08** (0.04)	-0.01 (0.04)	0.09* (0.05)	0.04 (0.03)	0.12*** (0.04)	0.09** (0.05)	0.32*** (0.06)	0.16*** (0.06)	0.09*** (0.03)	0.00*** (0.00)	-0.03 (0.03)	0.02 (0.03)	-0.11 (0.08)	0.07** (0.03)	0.00 (0.00)	0.03 (0.03)

Note: Standard errors are in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$. Variable definitions are provided in Tables 2 and 3.

^a. The dependent variable is an ordinal variable measuring the perceived level of disaster preparedness. Level 0 is if the household is not prepared and they do not intend to prepare in the next year. Level 1 is if the household is not prepared but intends to start preparing in the next year. Level 2 is if the household is not prepared but intends to get prepared in the next six months. Level 3 is if the household has been prepared for the last year. Level 4 is if the household has been prepared for more than a year and continues preparing.

Of particular interest in this study is the impact of the different sources of information on the perceived level of disaster preparedness (Model A). All of the information sources except television have a significant impact on the perceived level of disaster preparedness, but results do vary by information source and region, supporting Hypotheses H_{1b_1} to H_{1f_1} overall. Looking at the effect of information sources on the perceived level of wildfire preparedness (Model B), we see that information sources significantly increased the perceived level of wildfire preparedness, supporting Hypotheses H_{1a_1} to H_{1f_1}, except H_{1d_1}. That is, the different information sources all play a role in influencing general disaster preparedness in high-risk wildfire regions as well as directly for wildfire preparedness. These are only sign effects, though, indicating the likelihood (positive or negative) of being in a specific preparedness category. When statistically significant, almost all coefficients were positive in sign, indicating a higher likelihood of being in a higher preparedness category. This was not the case for public announcements in the GP. The sign here was negative, indicating public announcements reduced wildfire and disaster preparedness. Thus, interaction effects of information sources with region indicate different information sources influence disaster and wildfire preparedness differently by region. Based on coefficient estimates from the ordered probit model, in the MW states, television and radio, internet, print, public announcements, networks and other sources all influenced wildfire preparedness, while in the GP states, only public announcements and networks significantly influenced wildfire preparedness. These findings provide some evidence for differences between regions, supporting hypotheses H_{1a_2}, H_{1b_2}, H_{1e_2}, and H_{1f_2}.

To further examine hypotheses H_{1a_2} to H_{1f_2}, we assess the marginal effects for the different information sources from the perceived level of disaster preparedness model using the estimated marginal effects in Table 3.5. Results by region do vary. The marginal effects provide

signs and magnitudes of the influence of information sources on preparedness. That is, the marginal effects tell us the change in the likelihood of being in a particular preparedness category given an information source was adopted. Given the use of interactions in the model, we can estimate MEs for both the GP and MW regions. Results point to some significant differences. For the MW region, all the information sources except television/radio had positive and statistically significant MEs on the perceived levels of disaster preparedness. For the GP region, only three of the information sources, i.e. the internet, networks, and public announcements, had a statistically significant ME on the perceived levels of disaster preparedness. This shows that the magnitudes of effects differ by region, as well. Of particular interest was the result that public announcements had an overall negative and statistically significant impact on the GP. That is, in the MW, public announcements increased the likelihood of being in the highest preparedness category level by 32%. In contrast, in the GP, public announcements decreased the likelihood of being in the highest preparedness category level by 24%. Differences arise across preparedness categories for the ME for the internet, print, and networks as well, but signs of the ME are the same, providing support for hypotheses H_{1e_2} and H_{1f_2} and disagreeing with hypotheses H_{1b_2} and H_{1c_2} , due to the fact that these information sources have a greater impact in the GP than the MW. The ME for television and radio for both regions were not statistically significant for both regions, providing a lack of support for hypothesis H_{1a_2} .

Examining the ME in Table 3.5 for Model A for the MW region specifically, public announcements increased the likelihood of being in the highest preparedness category by 32%, then networks at 16%, followed by the internet at 12%, and lastly by print and other sources at 9%. In contrast, public announcements decreased the likelihood of being in the lowest preparedness category by 8%, followed by networks at 5%, the internet at 4%, and by print and other sources at

3%. Examining the ME for Model A for the GP region specifically, public announcements decreased the likelihood of being in the highest preparedness category by 24% and increased it by 26% if the information was obtained from the networks and by 17% if the source was the internet. In contrast, public announcements had no effect on the likelihood of being in the lowest preparedness category and the likelihood decreased by 4% and 5% if the information was obtained from the internet and networks, respectively.

Another ME of interest is the prior wildfire experience. ME estimates in Table 3.5 consistently provide support that households that experienced wildfire in the past were more likely to be in the highest preparedness category (already prepared for last year and continue to prepare) and less likely to be in all other preparedness categories, irrespective of the region. ME for being in the highest preparedness category for prior wildfire experience were slightly higher for the GP at 13% and 9% for the MW.

The timing of the FEMA survey, which corresponds to areas that had been impacted by wildfire, had a negative and statistically significant effect on the likelihood of the perceived level of disaster preparedness, specifically in 2018 relative to 2020, but no significant difference was observed for the year and area interaction. However, we did not observe any significant difference for any of the years for the perceived level of wildfire preparedness, nor an interaction of year with area. Of interest is that the ME for each year (relative to 2020) decreases in magnitude in both regions. This result may point toward an upward trend over time in disaster preparedness, but further research is needed to establish this relationship.

Examination of demographic factors shows that age (+) and education (+) were the only demographic characteristics that were statistically significant in the perceived level of disaster

preparedness (Model A). For the perceived level of wildfire preparedness (Model B), age was the only significant variable and had a positive effect.

4.3 Influence of Information Flows on Adoption of Defensible Space

We used a probit model to determine the factors that drive the adoption of defensible space and how the influence of information flows varies across space. The model results are shown in Table 3.6. We find that networks, public announcements, and other sources have a positive and significant impact on the adoption of defensible space. However, we do not observe any significance difference in sign effect between MW and GP, as none of the interaction effects of GP with each information source was significant. As for the rest of the independent variables, experience with wildfire, age, and being a homeowner had a positive and significant effect on the adoption of defensible space, with the rest of the independent variables being insignificant.

Table 3.6. Probit Estimation Results for the Adoption of Defensible Space

Variables	Adoption of defensible space
GP	-0.56 (0.62)
2018	0.12 (0.13)
2019	0.04 (0.13)
GP*2018	0.77 (0.63)
GP*2019	0.37 (0.63)
Other sources	0.39** (0.17)
Other sources*GP	-0.09 (0.80)
Television/radio	0.05 (0.10)
Television/radio*GP	0.10 (0.28)

Internet	0.08 (0.12)
Internet*GP	-0.17 (0.35)
Print	0.19 (0.15)
Print*GP	-0.42 (0.49)
Public	0.52** (0.22)
Public*GP	-0.73 (0.55)
Networks	0.33* (0.19)
Networks*GP	0.74 (0.63)
Exp	0.45*** (0.11)
Exp*GP	-0.18 (0.28)
Age	0.01** (0.00)
Fem	0.16 (0.10)
Own	0.32*** (0.11)
Others	0.37 (0.32)
Educ	-0.02 (0.11)
Moinc	0.00 (0.00)
White	0.03 (0.11)
Constant	-0.58*** (0.19)
Log Likelihood	-484.05
Pseudo R ²	0.08
AIC	1022.09

Observations	823
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Note: Asymptotic standard errors are in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$. The dependent variable is a binary variable indicating 1 if the household has adopted a defensible space and 0 otherwise.

To determine the difference in magnitude of information flows across space, we estimated ME, and the results are shown in Table 3.7. The impact of networks on increasing the adoption of defensible space was higher in the GP compared to the MW. Access to disaster preparedness information from networks increased the adoption of defensible space by 33% in GP and 10% in MW. The rest of the information sources had no significant effect on the adoption of defensible space in the GP. However, in the MW, receiving information on disaster preparedness from public announcements and other sources increased the adoption of defensible space by 16% and 12%, respectively, with the remaining information sources having no significant effect on the adoption of defensible space. It was interesting to find that past experience with wildfire had a positive and highly significant effect on MW, but it was insignificant in the GP. Experience with wildfire increased the adoption of defensible space in MW by 15%.

Table 3.7. Marginal Effects for Each Explanatory Variable on the Adoption of Defensible Space for the Mountainous Western States (MW) and the Great Plains (GP)

Variables	Marginal effects for Great Plains States (GP) (Part A)	Marginal effects for the Mountainous Western States (MW) (Part B)
GP	-0.13 (0.09)	-0.13 (0.09)
2018	0.31 (0.22)	0.04 (0.04)
2019	0.15 (0.22)	0.01 (0.04)
Other sources	0.10 (0.26)	0.12** (0.05)
Television/radio	0.05 (0.09)	0.02 (0.03)
Internet	-0.03 (0.11)	0.03 (0.04)
Print	-0.08 (0.16)	0.06 (0.05)
Public	-0.07 (0.18)	0.16*** (0.06)

Networks	0.33** (0.14)	0.10* (0.05)
Exp	0.09 (0.09)	0.15*** (0.04)
Age	0.00** (0.00)	0.00** (0.00)
Fem	0.05 (0.03)	0.05 (0.03)
Own	0.11*** (0.04)	0.11*** (0.04)
Others	0.13 (0.11)	0.13 (0.10)
Educ	-0.01 (0.04)	-0.01 (0.04)
Moinc	0.00 (0.00)	0.00 (0.00)
White	0.01 (0.04)	0.01 (0.04)

Note: Standard errors are in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$. Variable definitions are provided in Tables 2 and 3. The dependent variable is a binary variable indicating 1 if the household has adopted a defensible space and 0 otherwise.

4.4 Perceived Confidence Level to Prepare for a Wildfire and Disaster and Perceived Likelihood of a Wildfire Event Occurring

Table 3.8, Model A, presents estimation results for the bivariate probit model examining the joint likelihood of a wildfire event occurring and the perceived confidence level to prepare for a disaster.³² In Model B, we estimate a bivariate probit model similar to Model A, but replace the perceived confidence level to prepare for a disaster (the dependent variable) with the perceived confidence level to prepare for a wildfire. Although both of the Models are in a wildfire context, Model B specifically focuses on the perceived confidence in preparedness for a wildfire event specifically. Recall, a bivariate model was adopted due to the simultaneous determination of

³² In the appendix in Appendix Table C.2, we also show the results when we estimate the bivariate probit model using a single or primary source of disaster preparedness information rather than both sources listed in the survey data. We observe the same significant variables and signs for most, as when both information sources are considered (if provided by respondents).

perceptions about wildfire risk and confidence in being prepared. Estimation results indicate that these two factors were not statistically correlated (i.e. the tetrachoric correlation coefficient, rho, is small and not significantly different from zero) for Model A, but it is significant for Model B (p-value<0.05). That is, perceiving a higher likelihood of a wildfire event occurring in your local area does not significantly influence a respondent's perceived confidence level to prepare for a disaster, but it does have a significant effect on a respondent's perceived confidence level to prepare for a wildfire.

Table 3.8. Two Bivariate Probit Models Estimation Results for Joint Modeling of the Probability of a High Likelihood of a Wildfire Event Occurring and Probability of Having a High Perceived Confidence Level to Prepared for a Disaster (Model A) and the Probability of a High Likelihood of a Wildfire Event Occurring and Probability of Probability of Having a High Perceived Confidence Level to Prepared for a Wildfire (Model B) for Entire Study Region

Bivariate Probit Model				
Variables	Model A		Model B	
	Part 1a Estimated probability of a high likelihood of a wildfire event occurring	Part1b Estimated probability of having a high perceived confidence level to prepare for a disaster	Part 2a Estimated probability of a high likelihood of a wildfire event occurring	Part2b Estimated probability of having a high perceived confidence level to prepare for a wildfire
GP	0.09 (0.65)	1.08* (0.64)	-0.50* (0.27)	-0.01 (0.27)
2018	0.22* (0.13)	-0.08 (0.13)	0.29* (0.15)	0.04 (0.14)
2019	0.00 (0.13)	-0.01 (0.13)		
GP* 2018	-0.13 (0.65)	-0.61 (0.64)	0.32 (0.30)	0.26 (0.29)
GP* 2019	-0.50 (0.65)	-0.49 (0.64)		
Other sources	0.43** (0.17)	0.16 (0.16)	0.74** (0.34)	0.14 (0.26)

Other sources*GP	0.59 (0.75)	-0.68 (0.73)	0.27 (0.81)	0.27 (0.70)
Television/r adio	-0.14 (0.10)	0.22** (0.10)	-0.26* (0.15)	0.17 (0.14)
Television/r adio*GP	0.12 (0.28)	-0.10 (0.27)	0.30 (0.31)	-0.13 (0.30)
Internet	0.05 (0.12)	0.25** (0.12)	-0.01 (0.18)	0.38** (0.16)
Internet*G P	-0.14 (0.37)	-0.06 (0.34)	-0.18 (0.40)	-0.56 (0.39)
Print	-0.12 (0.15)	-0.02 (0.14)	-0.31 (0.20)	0.12 (0.19)
Print*GP	-0.05 (0.47)	-0.81 (0.51)	0.07 (0.52)	-0.13 (0.54)
Public	0.74*** (0.23)	0.35* (0.18)	1.00*** (0.31)	0.04 (0.23)
Public*GP	-0.50 (0.62)	-0.55 (0.61)	-0.91 (0.65)	-0.30 (0.63)
Networks	0.23 (0.18)	0.71*** (0.17)	0.19 (0.23)	0.53** (0.22)
Networks* GP	-0.17 (0.52)	-0.20 (0.47)	-0.20 (0.55)	-0.15 (0.53)
Exp	1.00*** (0.11)	0.51*** (0.11)	0.80*** (0.16)	0.36** (0.14)
Exp*GP	0.24 (0.30)	-0.59** (0.27)	0.48 (0.33)	0.43 (0.30)
Age	-0.01*** (0.00)	0.00 (0.00)	-0.00 (0.00)	0.01 (0.00)
Fem	0.19* (0.10)	-0.19** (0.09)	0.10 (0.13)	-0.13 (0.12)
Own	0.12 (0.11)	0.05 (0.11)	0.14 (0.15)	0.20 (0.15)
Others	0.22 (0.32)	0.35 (0.29)	-0.56 (0.46)	0.32 (0.41)
Educ	-0.07 (0.11)	0.19* (0.11)	0.01 (0.14)	0.17 (0.13)
Moinc	-0.00* (0.00)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
White	-0.04 (0.12)	0.16 (0.12)	-0.25 (0.17)	0.25 (0.18)
Constant	0.13	-1.12***	0.22	-1.29***

	(0.19)	(0.20)	(0.26)	(0.26)
Rho (tetrachoric correlation)		0.07		0.17**
		(0.06)		(0.08)
Log Likelihood		-1000.44		-584.39
AIC		2110.87		1270.78
Observations		836		487

Note: Asymptotic standard errors are in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$.

The influence of factors on the perceived likelihood of a wildfire event occurring is presented in Table 3.8. The column labelled Model A Part 1b in Table 3.8 shows the influence of factors influencing the likelihood of having a high perceived confidence level to prepare for a disaster. Based on coefficient estimates alone, previous wildfire experience and information sources from television/radio, the internet, networks, and public announcement had a statistically significant influence on a household's perceived confidence level to prepare for a disaster, providing support for hypotheses H_{2a_1}, H_{2b_1}, H_{2c_1}, and H_{2d_1}, but the sign effect did not seem to vary across the GP compared to MW, providing a lack of support for hypotheses H_{2a_2}, H_{2b_2}, H_{2c_2}, H_{2d_2}, H_{2e_2}, and H_{2f_2}.

In Model B, we used the perceived likelihood of a wildfire event occurring and the perceived confidence level to prepare for a wildfire as the two dependent variables for the bivariate probit model. We do not have any observations for 2020; therefore, 2019 becomes the base year. The result of Model B is shown in Table 3.8. Model B Part 2b shows the influence of prior wildfire experience and information sources on a household's perceived confidence level to prepare for a wildfire. Experience with wildfire had a positive effect on the perceived confidence level to prepare for a wildfire. As for information sources, only the internet and networks had a significant

effect on a household's perceived confidence level to prepare for a wildfire, and the effect was positive, consistent with hypotheses H_{2b_1} and H_{2c_1} . However, we do not observe any significance difference between GP and MW in the effect of information sources on the perceived confidence level to prepare for a wildfire, contradicting hypotheses H_{2a_2} , H_{2b_2} , H_{2c_2} , H_{2d_2} , H_{2e_2} , and H_{2f_2} .

To go deeper into assessing the marginal effect of different information sources, we estimated region-specific marginal effects of the bivariate probabilities with respect to the likelihood of alternative joint outcomes of perceiving a higher likelihood of a wildfire occurring and perceiving being highly confident of being prepared for a wildfire or disaster. These marginal effects are presented in Table 3.9 for Model A. Part A is the ME for the GP region, and Part B is for the MW region. The first row (Group 1) in Part A shows those respondents who perceived a high likelihood of a wildfire event occurring and had a high perceived confidence level to prepare for a disaster in the GP. Past experience with wildfire increased the likelihood of being in this group by 17%. Only information sources from print had a negative effect on being in Group 1 by 17%, with the rest of the information sources having no impact. ME for the MW region shows other sources, the internet, networks, and public announcements having a positive and statistically significant influence on respondents in this group, with networks having the largest marginal effect (19%), public announcements having the second highest (17%), followed by other sources (9%), and the internet having the least impact (6%). See Part B in Table 3.9 for the results. In the MW, past experience with wildfire increased the likelihood of being in this group by 25%.

Table 3.9. Marginal Effects of the Joint Modeling of the Probability of a High Likelihood of a Wildfire Event Occurring and Probability of Having a High Perceived Confidence Level to Prepared for a Disaster (Model A) and the Probability of a High Likelihood of a Wildfire Event Occurring and Probability of Having a High Perceived Confidence Level to Prepared for a Wildfire (Model B) from the Bivariate Models for Each Explanatory Variable for Each Region

Variables	GP	2018	2019	Other Sources	Television/ Radio	Internet	Print	Public	Networks	Exp	Age	Fem	Own	Others	Educ	Moinc	White
ME for the joint likelihood of a wildfire event occurring and the perceived confidence level to prepare for a disaster estimated for the Great Plains (GP) (Model A: Part A)																	
Pr($y_1=1$, $y_2=1$)	0.02	-0.14	-0.18	-0.01	0.02	0.03	-0.17*	-0.01	0.12	0.17**	-0.00	-0.01	0.03	0.11	0.03	0.00	0.03
(Group 1)	(0.08)	(0.19)	(0.18)	(0.20)	(0.07)	(0.09)	(0.09)	(0.15)	(0.13)	(0.08)	(0.00)	(0.03)	(0.03)	(0.09)	(0.03)	(0.00)	(0.03)
Pr($y_1=1$, $y_2=0$)	-0.03	0.17	0.02	0.30	-0.03	-0.05	0.12	0.08	-0.10	0.23***	-0.00**	0.07***	0.01	-0.04	-0.05*	-0.00*	-0.04
(Group 2)	(0.07)	(0.16)	(0.16)	(0.22)	(0.07)	(0.08)	(0.13)	(0.16)	(0.10)	(0.08)	(0.00)	(0.03)	(0.03)	(0.07)	(0.03)	(0.00)	(0.03)
Pr($y_1=0$, $y_2=1$)	0.07	-0.11	-0.00	-0.17**	0.02	0.04	-0.11	-0.06	0.07	-0.20***	0.00**	-0.06***	-0.01	0.02	0.04*	0.00*	0.03
(Group 3)	(0.06)	(0.14)	(0.15)	(0.07)	(0.05)	(0.08)	(0.08)	(0.10)	(0.11)	(0.06)	(0.00)	(0.02)	(0.02)	(0.07)	(0.02)	(0.00)	(0.02)
Pr($y_1=0$, $y_2=0$)	-0.06	0.08	0.16	-0.12	-0.01	-0.02	0.16	-0.01	-0.08	-0.20***	0.00	-0.00	-0.03	-0.08	-0.02	0.00	-0.02
(Group 4)	(0.05)	(0.12)	(0.13)	(0.12)	(0.06)	(0.08)	(0.13)	(0.13)	(0.09)	(0.06)	(0.00)	(0.02)	(0.03)	(0.06)	(0.03)	(0.00)	(0.03)
ME for the joint likelihood of a wildfire event occurring and the perceived confidence level to prepare for a disaster estimated for the Mountainous Western States (MW) (Model A: Part B)																	
Pr($y_1=1$, $y_2=1$)	0.02	0.01	-0.00	0.09*	0.03	0.06**	-0.02	0.17***	0.19***	0.25***	-0.00	-0.02	0.02	0.10	0.03	0.00	0.03
(Group 1)	(0.08)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.06)	(0.05)	(0.03)	(0.00)	(0.02)	(0.03)	(0.08)	(0.03)	(0.00)	(0.03)
Pr($y_1=1$, $y_2=0$)	-0.03	0.07*	0.00	0.05	-0.08**	-0.04	-0.02	0.05	-0.12**	0.09***	-0.00**	0.08***	0.01	-0.03	-0.06*	-0.00*	-0.04
(Group 2)	(0.07)	(0.04)	(0.04)	(0.05)	(0.03)	(0.03)	(0.04)	(0.06)	(0.05)	(0.03)	(0.00)	(0.03)	(0.03)	(0.09)	(0.03)	(0.00)	(0.04)
Pr($y_1=0$, $y_2=1$)	0.07	-0.04*	-0.00	-0.03	0.05**	0.03	0.01	-0.05*	0.06*	-0.07***	0.00**	-0.05***	-0.01	0.02	0.03*	0.00*	0.03
(Group 3)	(0.06)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.00)	(0.02)	(0.02)	(0.06)	(0.02)	(0.00)	(0.02)
Pr($y_1=0$, $y_2=0$)	-0.06	-0.04	-0.00	-0.11***	-0.00	-0.05	0.03	-0.18***	-0.14***	-0.27***	0.00*	-0.01	-0.03	-0.09	-0.01	0.00	-0.01
(Group 4)	(0.05)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.00)	(0.02)	(0.03)	(0.07)	(0.03)	(0.00)	(0.03)
ME for the joint likelihood of a wildfire event occurring and the perceived confidence level to prepare for a wildfire estimated for the Great Plains (GP) (Model B: Part C)																	

Variables	GP	2018	2019	Other Sources	Television/ Radio	Internet	Print	Public	Networks	Exp	Age	Fem	Own	Others	Educ	Moinc	White
Pr(y ₁ =1, y ₃ =1) (Group 1)	0.01 (0.04)			0.22 (0.20)	0.01 (0.07)	-0.06 (0.08)	-0.03 (0.11)	-0.04 (0.14)	0.07 (0.13)	0.37*** (0.08)	0.00 (0.00)	-0.01 (0.03)	0.06 (0.04)	-0.03 (0.09)	0.04 (0.03)	0.00 (0.00)	0.02 (0.04)
Pr(y ₁ =1, y ₃ =0) (Group 2)	-0.08* (0.04)			0.06 (0.19)	0.00 (0.07)	-0.00 (0.09)	-0.04 (0.12)	0.07 (0.16)	-0.08 (0.11)	0.05 (0.08)	-0.00* (0.00)	0.04 (0.03)	-0.01 (0.04)	-0.14* (0.08)	-0.03 (0.04)	-0.00 (0.00)	-0.10* (0.05)
Pr(y ₁ =0, y ₃ =1) (Group 3)	0.01 (0.03)			-0.08 (0.09)	-0.00 (0.05)	-0.00 (0.07)	0.03 (0.10)	-0.05 (0.09)	0.06 (0.11)	-0.08 (0.05)	0.00* (0.00)	-0.03 (0.02)	0.01 (0.03)	0.14 (0.11)	0.02 (0.02)	0.00 (0.00)	0.06* (0.03)
Pr(y ₁ =0, y ₃ =0) (Group 4)	0.05 (0.04)			-0.21** (0.10)	-0.01 (0.07)	0.06 (0.09)	0.04 (0.13)	0.02 (0.14)	-0.06 (0.11)	-0.34*** (0.06)	0.00 (0.00)	0.00 (0.03)	-0.05 (0.04)	0.03 (0.12)	-0.03 (0.03)	0.00 (0.00)	0.01 (0.04)
ME for the joint likelihood of a wildfire event occurring and the perceived confidence level to prepare for a wildfire estimated for the Mountainous Western States (MW) (Model B: Part D)																	
Pr(y ₁ =1, y ₃ =1) (Group 1)	0.01 (0.04)			0.12 (0.09)	0.00 (0.04)	0.09* (0.05)	-0.02 (0.05)	0.12 (0.08)	0.15** (0.07)	0.20*** (0.04)	0.00 (0.00)	-0.02 (0.03)	0.06 (0.04)	-0.02 (0.10)	0.04 (0.04)	0.00 (0.00)	0.03 (0.05)
Pr(y ₁ =1, y ₃ =0) (Group 2)	-0.08* (0.04)			0.09 (0.09)	-0.09** (0.04)	-0.09** (0.05)	-0.09* (0.05)	0.16** (0.08)	-0.09 (0.06)	0.07 (0.04)	-0.00* (0.00)	0.05 (0.04)	-0.02 (0.04)	-0.17* (0.09)	-0.04 (0.04)	-0.00 (0.00)	0.11* (0.05)
Pr(y ₁ =0, y ₃ =1) (Group 3)	0.01 (0.03)			-0.07* (0.04)	0.06** (0.03)	0.06 (0.03)	0.06 (0.04)	-0.10*** (0.03)	0.04 (0.05)	-0.06** (0.03)	0.00* (0.00)	-0.03 (0.02)	0.01 (0.03)	0.14 (0.11)	0.02 (0.02)	0.00 (0.00)	0.06* (0.02)
Pr(y ₁ =0, y ₃ =0) (Group 4)	0.05 (0.04)			-0.14*** (0.05)	0.03 (0.04)	-0.05 (0.04)	0.04 (0.05)	-0.18*** (0.04)	-0.10** (0.05)	-0.20*** (0.03)	0.00 (0.00)	-0.00 (0.03)	-0.05 (0.04)	0.05 (0.12)	-0.02 (0.04)	0.00 (0.00)	0.02 (0.04)

Note: Asymptotic standard errors are in parentheses. *** denotes p<0.01, ** denotes p<0.05, and * denotes p<0.1.

Another group of interest are respondents who perceived a high likelihood of a wildfire event occurring but had a low perceived confidence level to prepare for a disaster (Group 2). For this group, being in the GP (Part A; Table 3.9) and having prior wildfire experience were about 23% more likely to be in this group, while information sources had no effect on the likelihood of being in this group in the GP. Being in MW and having experience with wildfire increased the likelihood of being in this group by 9% (Table 3.9, Part B). Except for networks and television/radio, all other information sources had no effect on being in Group 2 for MW. Access to information sources reduced the probability of being in this group by 12 percent and 8 percent, respectively.

Group 3 in Table 3.9, Model A, shows those respondents who had a lower perceived likelihood of a wildfire event occurring in their local area, but have a high perceived confidence level to prepare for a disaster. Experience with wildfire in the past decreased the likelihood of being in this group by about 20% in the GP and 7% in the MW (Table 3.9, Part A and B, respectively). Respondents in the GP are 17% less likely to be in this group if they obtain disaster preparedness information from other sources, with the rest of the information sources being insignificant. In the MW, television/radio, network, and public announcement had a statistically significant ME of being in this group. Obtaining your disaster preparedness information from the television/radio and the internet increased the likelihood of being in this group by 5% and 6%, respectively, and decreased if the information was obtained from public announcements by 5%.

The last group, Group 4 in Table 3.9 Model A, shows those respondents who have a low perceived likelihood of a wildfire event occurring and a low perceived confidence level to prepare for a disaster. Table 3.9 Part A shows the ME for the GP, and Part B for the MW. Experience with wildfire in the past decreased the likelihood of being in this group by about 20% in the GP and

27% in the MW. In the GP, no information source had a significant effect on being in this group. Except for television/radio, print, and internet, receiving any other disaster preparedness information sources in the MW decreased the probability of being in this group compared to no information, and all the marginal effects are significant at a 1% level of significance. Access to disaster preparedness information decreases the probability of being in this group from 11 to 18 percent for other sources, public announcement, and networks.

Table 3.9, Part C, shows the ME for being in the GP for all the information sources and past experience with a wildfire for a bivariate model using the perceived likelihood of a wildfire event occurring and the perceived confidence level to prepare for a wildfire (Model B). Model B, Part D shows the MEs for the MW, with the same dependent variables as Part C. We define Group 1 as those respondents who perceived a high likelihood of a wildfire event occurring and had a high perceived confidence level to prepare for a wildfire. Past experience with wildfire increased the likelihood in Group 1 by 37% in the GP and 20% in MW. No information sources had a significant effect on being in Group 1 for the GP, but it was the internet and networks for the MW. Having access to disaster preparedness information in the MW from the internet and networks increased the probability of being in Group 1 by 9% and 15%, respectively.

Group 2 Model B are those respondents who perceived a high likelihood of a wildfire event occurring but had a low perceived confidence level to prepare for a wildfire. Past experience with wildfire had no effect on the likelihood of being in this group for both the GP and MW (Table 3.9, Part C and Part D, respectively). Information on disaster preparedness still had no effect on being in this group in the GP, but it was significant for some information sources in the MW. Access to information sources in the MW from public announcements increased the likelihood of being in

this group by 16%, but it decreased by 9% if the information was obtained from television/radio, internet, or print.

The third group, Group 3, were respondents who had a lower perceived likelihood of a wildfire event occurring in their local area but had a high perceived confidence level to prepare for a wildfire (Table 3.9; Model B). Part C shows the ME for the GP, and Part D for the MW. Past experience with a wildfire decreased the likelihood of being in this group by 6% in the MW but was insignificant for the GP. Information sources still had no effect on being in this group for the GP. However, in the MW access of information from other sources and public announcements decreased the likelihood of being in this group by 7% and 10%, respectively and increased the likelihood of being in this group by 6% if the information was obtained from television/radio.

The final group, Group 4 in Table 3.9, Model B, consists of respondents who have a low perceived likelihood of a wildfire event occurring and a low perceived confidence level to prepare for a wildfire. The ME are shown in Part C for the GP and Part D for the MW. Past experience with a wildfire decreased the likelihood of being in this Group by 34% in the GP and 20% in the MW. Only information from other sources decreased the likelihood of being in this group by 21% for the GP. For the MW, information sources from the networks, other sources, and public announcements negatively influenced the likelihood of being in this group. The associated MEs were 10%, 14%, and 18%, respectively.

In addition to perceptions about wildfire occurrence, demographic variables that significantly influenced the perceived confidence level to prepare for a disaster were college degree (+) and race (-). For the perceived confidence level to prepare for a wildfire, although previous wildfire experience had a significant and positive effect, there was no significant

difference between the MW and GP. None of the demographic variables had a significant effect on the perceived confidence level to prepare for a wildfire.

4.4 Discussion

There was no real difference between respondents in the GP and MW with respect to the stated levels of perceived level of wildfire and disaster preparedness or the perceived confidence level to prepare for a wildfire or disaster. This was an unexpected finding since much of the focus on wildfires has been on the MW region. Overall, about 45% to 46% of households perceived they were in the highest preparedness category for wildfire and disaster preparedness. This is greater than the third of households in general that are prepared for a disaster in the U.S. as indicated in the literature. This higher preparedness may result from surveying households in areas with high wildfire risk, so there may be some sample selection biasing this estimate upwards. Yet, there still exists room for improvement. Only 39% and 43% of respondents indicated that they were confident that they were prepared for a disaster or wildfire, respectively.

Approximately 48% of respondents in the GP indicated they did not use any of the information sources examined, compared with 27% in the MW. The low number of respondents that have used the different information sources, ranging from 8% to 41% for disaster preparedness information, indicates a strong opportunity to further improve education and outreach for wildfire and disaster preparedness. Internet, print, networks, public announcement, and other sources (email, billboards, reverse 911, amongst other sources) increased the perceived level of wildfire and disaster preparedness. However, television/ radio had a positive effect on only the perceived level of wildfire preparedness, and this may be due to television and radio providing real-time information when an area is faced with or threatened by a specific disaster, such as wildfire. In the MW, the public announcements, networks, internet, print, and other sources increased the perceived level

of disaster preparedness to the highest preparedness category of preparedness by 32%, 16%, 12%, 9%, and 9%, respectively. This may arise due to the significant efforts from both experts and non-expert sources across multiple information sources about wildfire risk in fire-prone areas in the MW region (Brenkert-Smith et al. 2013). But for the GP, only the internet and networks increased the perceived level of disaster preparedness to the highest preparedness category by 17% and 26%, respectively, and decreased by 24% if the information was obtained from public announcements. Using the adoption of defensible space as an example of wildfire preparedness, only access to information from networks increased the adoption of defensible space by 33% in the GP and in the MW, public announcement and other sources increased the adoption of defensible space by 16% and 12%, respectively. These findings may show the effect of the disparity in the allocation of disaster resources, as households in GP states need to invest time and effort to look for information that may not be readily available. The negative effect of the public announcement was unexpected, and the reason may be a lack of trust due to a lack of sufficient funding to organize program on disaster preparedness for the public in the GP, building trust among the community members. For example, a study by Boland et al. (2025) in North and South Dakota found that ranching landowners did not trust information from the USDA Forest Service. McCaffrey (2015) attributes that a pathway to increase wildfire preparedness across geographic areas and households is to facilitate the development of relationships among community members within themselves and with fire personnel through encouraging information exchange, which should take into account the local knowledge and context. This would further build on the positive influence of networks, as well. It is important to contextually tailor wildfire information outreach approaches since fire behavior varies across local, spatial, and temporal scales (McCaffrey et al. 2020).

Disaster preparedness information from the internet and networks also changes the perceived confidence level to prepare for a wildfire or disaster. However, information sources from television/radio and public announcements only significantly influenced the perceived confidence level to prepare for a disaster. It may be that information sources from television/radio and public announcements provide disaster preparedness information when a wildfire event is imminent, and this may not provide enough time to prepare for a wildfire event, hence the insignificant effect on the perceived confidence level to prepare for a wildfire. Looking at the ME of information sources, we see that respondents who receive disaster preparedness information from the internet and networks were more likely to belong to the group who perceived a high likelihood of a wildfire event occurring and had a high perceived confidence level to prepare for a wildfire or disaster only for MW, but the effect was insignificant for GP. The ME ranged between 6% and 19%. The insignificant effect of information sources on the GP may be due to limited information sources in the GP.

Prior wildfire experience played a significant role in the perceived level of wildfire and disaster preparedness irrespective of the region, but the effect was much higher on the perceived level of wildfire preparedness compared to the perceived level of disaster preparedness. As expected, wildfire experience also had a statistically significant influence on the perceived confidence level to prepare for a wildfire or disaster. The perceived confidence level to prepare for a disaster was not significantly correlated with the perceived likelihood of a wildfire event occurring in a respondent's local area, but it was significant for the perceived confidence level to prepare for a wildfire and the perceived likelihood of a wildfire event occurring. ME for both the bivariate probit model indicate that previous wildfire experience influences the likelihood of a respondent being in the group that perceived a high likelihood of another wildfire occurring in

their local area and having a high perceived confidence level to prepare for a wildfire or disaster, irrespective of the region. Other studies have shown that confidence levels increase with exposure to wildfire (Adhikari et al. 2023; Paveglio et al. 2015; Wilson et al. 2011). Studies have also shown that experience with wildfire can influence the adoption of wildfire mitigation practices (T.K. McGee 2011; Jarrett et al. 2009; Paveglio et al. 2015; Winter and Fried 2000). The perceived confidence level to prepare for a disaster depends on experience in containing wildfires. People can lose their perceived confidence level to prepare for a disaster if they experience a loss of property (Winter and Fried 2000; Tara K. McGee et al. 2009; Tara K. McGee and Russell 2003). Given these findings, using the appropriate information channel may increase confidence in disaster preparedness among community members who have been faced with wildfires and believe they are at risk of future wildfires. The government just needs to invest resources in disaster education using the region-specific information channel that has an impact on disaster preparedness.

A strong takeaway from our findings is that we need to continue to utilize more than one information source and pathways to improve wildfire and disaster preparedness and confidence, both in the GP and MW regions of the U.S. Access to wildfire information through different sources is important for exposure to different wildfire mitigation strategies (McCaffrey 2004). More diverse sources can provide more specialized wildfire information, enhancing the adoption of wildfire mitigation and preparedness strategies (Brenkert-Smith et al. 2012) and influencing how much is invested in wildfire suppression in a region (G. H. Donovan et al. 2011; Eissensee and Stromberg 2007). When advocating for the uptake of disaster preparedness and mitigation strategies, the networks play a strong role in the GP and public announcements in the MW. In addition, we need to ensure that adequate resources are available to fund needed sources of

information, such as using the internet to broadcast disaster preparedness information, which may be a major source of disaster preparedness information in more rural communities. There is also a need for the government to build trust in the GP; without building the trust level, investment in educating the public about disaster preparedness through public announcements may not positively influence disaster preparedness. Research has shown that successful implementation of mitigation practices by a municipality requires sufficient funds, public, community leaders, and political support; taking advantage of windows of opportunity during wildfire outbreaks; and having different partnerships and collaborations for promotion and adoption of mitigation practices (Labossière and McGee 2017). Lastly, disaster preparedness information will only play a crucial role in shaping perceptions about the perceived confidence level to prepare for a disaster if households believe a future wildfire is imminent.

All the demographic variables that significantly affected the perceived level of wildfire and disaster preparedness were all positive. The significant variables were college degree and age for the perceived level of wildfire preparedness, and only age for the perceived level of disaster preparedness. Except for gender and college degree, all other demographic variables had no significant effect on the perceived confidence level to prepare for a disaster, while none of the demographic variables influenced the perceived confidence level to prepare for a wildfire. Muller and Schulte (2011) found no significant difference in housing tenure in determining wildfire preparedness, similar to what we observed in our study. The positive influence of education on wildfire mitigation practices has also been documented in the literature (Richmond 2021; Muller and Schulte 2011; Rivera 2021; Brenkert-Smith et al. 2012). Previous studies have also found that the perceived level of disaster preparedness is influenced by income and race, which was not observed in our study (Lindell and Prater 2000; Rivera 2021; Rao et al. 2022).

4.5. Limitations and Future Research

The study does have a number of limitations. First, we used an existing survey dataset from FEMA. The dataset does not provide detailed information on experiences with wildfires that would further help refine our analyses. The surveys do not indicate how often a household has experienced a wildfire or the type and amount of loss experienced. Previous studies have shown that wildfire preparedness depends on how many times a household has experienced a wildfire and the type of loss (Adhikari et al. 2023; Paveglio et al. 2015; Wilson et al. 2011; Winter and Fried 2000; Tara K. McGee et al. 2009; Tara K. McGee and Russell 2003). We expect a difference in the perceived level of wildfire and disaster preparedness and the perceived confidence level to prepare for a wildfire or disaster in households that have experienced a loss of life or financial loss compared to those households that have not incurred any type of loss.

The surveys also had little to no information on the various disaster mitigation practices households may have adopted based on each disaster preparedness information source. Knowing the number of disaster mitigation practices adopted and how their adoption is influenced by different information sources would be an important area of study. We observe significant findings of the effect of information sources on the perceived level of wildfire and disaster preparedness. However, we cannot tell if it is from the communication channel or the content of the information received and in cases where we have two sources of information, we do not know which source warrants them to take action. There is a need for evidence and causal based research that quantifies the effectiveness of each disaster preparedness information on the preparedness level (Clay et al. 2020).

Further research should incorporate the beliefs and attitudes on disaster preparedness and measure the trust levels of the alternative communication channels, which will further refine the

study. Studies have shown that perceptions about wildfires affect preparedness levels, whether it is controllable, uncontrollable or random (Winter and Fried 2000; Tara K. McGee and Russell 2003). There is also a need to study the effectiveness of alternative disaster communication channels based on rural and urban areas, which was not feasible in our study. A study by Okeukwu-Ogbonnaya et al. (2024) shows that the diffusion time of disaster preparedness information varies among different community types, i.e. rural, urban, and suburban areas, and we expect that the effect of communication channels will also vary.

5. Conclusion

Increased wildfire incidents in the western USA have become a significant and economically damaging yearly occurrence. Much of the focus on wildfires has been at the wildland-urban interface and in the mountainous west of the U.S., both by the government and in scholarly work; however, a relatively small share of this has been in the grassland-dominated regions of the Great Plains (GP). It is important to emphasize that there exists a disparity in the allocation of disaster funding and preparedness at the community level, as well as in wildfire characteristics between the GP and mountainous western regions (MW) of the U.S. Differences can also occur due to information availability, regional and time-specific factors, and wildfire experiences. This study adds to current research efforts by examining the influence of alternative information sources on the perceived level of wildfire and disaster preparedness of households between two different regions of the western U.S. that face high wildfire risk, using a 3-year wildfire-specific survey data set (2018-2020) from the Federal Emergency Management Agency (FEMA).

We find no significant difference in the perceived level of wildfire and disaster preparedness or the perceived confidence level to prepare for a wildfire or disaster among

households in GP compared to the MW. However, prior experience with wildfire and some of the disaster preparedness information sources play a significant role in shaping the perceived level of wildfire and disaster preparedness and the perceived confidence level to prepare for a wildfire or disaster. Influences are region-specific. The effect of prior wildfire experience on the perceived level of disaster preparedness and the perceived confidence level to prepare for a wildfire or disaster was positive and much higher in MW than in GP for only the perceived confidence level to prepare for a disaster. Public announcements were the strongest source of information in increasing disaster preparedness to the highest preparedness category in the MW, but the network served as the strongest information source for the GP. The same was observed for the effect of information sources on the adoption of defensible space. In order to have more impact on disaster preparedness, more than one region-specific information source should be used, and there is a need for mobilizing disaster resources, especially in regions that are faced with limited resources. Understanding the region-specific trends and significant information sources is critical to shaping future marketing, outreach and education efforts to enhance household disaster preparedness and response, especially for wildfires.

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Appendix A - Robustness Checks for the Mixed Effects Weibull Accelerated Failure Time

Model (AFTM)

Appendix Table A.1. Robustness Checks for Various Combinations of Interactions of Wildfire Experience and the Acreage of Expired CRP Parcels

	Model A Coeff	Model B Coeff	Model C Coeff	Model D Coeff	Model E Coeff	Model F Coeff
Clay	0.002 (0.005)	0.002 (0.005)	0.002 (0.005)	0.002 (0.005)	0.002 (0.005)	0.002 (0.005)
Silt	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
Kw factor	-0.782 (0.657)	-0.782 (0.657)	-0.775 (0.657)	-0.781 (0.657)	-0.783 (0.657)	-0.783 (0.657)
WEI	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Acres	-0.011** (0.004)	-0.011** (0.004)	-0.011** (0.004)	-0.011** (0.004)	-0.011** (0.004)	-0.011** (0.004)
Acres^2	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Class 2	-0.176 (0.137)	-0.176 (0.137)	-0.175 (0.136)	-0.176 (0.137)	-0.176 (0.137)	-0.176 (0.137)
Class 3	-0.093 (0.138)	-0.093 (0.138)	-0.092 (0.138)	-0.093 (0.138)	-0.093 (0.138)	-0.093 (0.138)
Class 4	-0.108 (0.142)	-0.108 (0.142)	-0.107 (0.142)	-0.108 (0.142)	-0.108 (0.142)	-0.108 (0.142)
Class 5	0.151 (0.373)	0.151 (0.373)	0.151 (0.373)	0.151 (0.373)	0.151 (0.373)	0.151 (0.373)
Class 6	0.023 (0.157)	0.022 (0.157)	0.022 (0.157)	0.022 (0.157)	0.022 (0.157)	0.022 (0.157)

	Model A Coeff	Model B Coeff	Model C Coeff	Model D Coeff	Model E Coeff	Model F Coeff
Class 7	-0.040 (0.200)	-0.041 (0.199)	-0.041 (0.199)	-0.041 (0.199)	-0.041 (0.200)	-0.041 (0.200)
Class 2* Acres	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)
Class 3* Acres	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)
Class 4* Acres	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)
Class 5* Acres	0.012 (0.013)	0.012 (0.013)	0.012 (0.013)	0.012 (0.013)	0.012 (0.013)	0.012 (0.013)
Class 6* Acres	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)
Class 7* Acres	0.007 (0.005)	0.007 (0.005)	0.007 (0.005)	0.007 (0.005)	0.007 (0.005)	0.007 (0.005)
	-	-	-	-	-	-
Laspeyres crop index	0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	-0.011*** (0.001)	0.011*** (0.001)	0.011*** (0.001)
T0=2012	1.873*** (0.076)	1.873*** (0.076)	1.873*** (0.076)	1.873*** (0.076)	1.873*** (0.076)	1.873*** (0.076)
T0=2013	1.546*** (0.071)	1.546*** (0.071)	1.546*** (0.071)	1.546*** (0.071)	1.546*** (0.071)	1.546*** (0.071)
T0=2014	1.361*** (0.070)	1.361*** (0.070)	1.361*** (0.070)	1.361*** (0.070)	1.361*** (0.070)	1.360*** (0.070)
T0=2015	1.168*** (0.089)	1.168*** (0.089)	1.169*** (0.089)	1.168*** (0.089)	1.168*** (0.089)	1.168*** (0.089)
T0=2016	1.047*** (0.093)	1.047*** (0.093)	1.047*** (0.093)	1.047*** (0.093)	1.047*** (0.093)	1.047*** (0.093)
T0=2017	0.902*** (0.095)	0.902*** (0.095)	0.902*** (0.095)	0.902*** (0.095)	0.902*** (0.095)	0.902*** (0.095)
T0=2018	0.829***	0.829***	0.830***	0.829***	0.829***	0.829***

	Model A Coeff	Model B Coeff	Model C Coeff	Model D Coeff	Model E Coeff	Model F Coeff
T0=2019	(0.058) 0.444***	(0.058) 0.444***	(0.058) 0.439***	(0.058) 0.445***	(0.058) 0.444***	(0.058) 0.444***
Mavetemp_10yrlag	(0.095) 0.349***	(0.095) 0.349***	(0.094) 0.349***	(0.095) 0.349***	(0.095) 0.349***	(0.095) 0.349***
Maveprep_10yrlag	(0.091) -0.016*	(0.091) -0.016*	(0.091) -0.016*	(0.091) -0.016*	(0.091) -0.016*	(0.091) -0.016*
Mavepdsi_10yrlag	(0.008) 0.056	(0.008) 0.056	(0.008) 0.056	(0.008) 0.057	(0.008) 0.056	(0.008) 0.056
Nearest wildfire	(0.041) -0.000	(0.041) -0.000	(0.041) -0.000	(0.041) -0.000	(0.041) -0.000	(0.041) -0.000
Megafire	(0.000) 0.355***	(0.000) 0.355***	(0.000) 0.355***	(0.000) 0.355***	(0.000) 0.355***	(0.000) 0.355***
	(0.109) -	(0.109) -	(0.109) -	(0.109) -	(0.109) -	(0.109) -
Megafire *Nearest megafire	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
	- 0.005***	- 0.005***	- 0.005***	- -0.005***	- 0.005***	- 0.005***
Perbuffer50m_crop	(0.001) -0.000	(0.001) -0.000	(0.001) -0.000	(0.001) -0.000	(0.001) -0.000	(0.001) -0.000
Perbuffer50m_developed	(0.001) 0.009***	(0.001) 0.009***	(0.001) 0.009***	(0.001) 0.009***	(0.001) 0.009***	(0.001) 0.009***
Perbuffer50m_water	(0.003) 0.008***	(0.003) 0.008***	(0.003) 0.008***	(0.003) 0.008***	(0.003) 0.008***	(0.003) 0.008***
Perbuffer50m_grass	(0.001) 0.023**	(0.001) 0.023**	(0.001) 0.023**	(0.001) 0.023**	(0.001) 0.023**	(0.001) 0.023**
Land valuation	(0.009) -0.001*	(0.009) -0.001*	(0.009) -0.001*	(0.009) -0.001*	(0.009) -0.001*	(0.009) -0.001*
Pop estimate	(0.001) 0.236***	(0.001) 0.236***	(0.001) 0.236***	(0.001) 0.236***	(0.001) 0.236***	(0.001) 0.236***
Acres_greater_1.55=0 * Megafire damage=0 * Percent parcel burnt						

	Model A Coeff	Model B Coeff	Model C Coeff	Model D Coeff	Model E Coeff	Model F Coeff
	(0.012)					
	-					
Acres_greater_1.55=0 *Megafire damage=1 * Percent parcel burnt	5.079***					
	(0.308)					
Acres_greater_1.55=1 * Megafire damage=0 * Percent parcel burnt	-0.013					
	(0.009)					
	-					
Acres_greater_1.55=1 *Megafire damage=1 * Percent parcel burnt	9.611***					
	(0.665)					
Acres_greater_1.55=0 *Megafire buffer damage=0 * Percent buffer burnt	-0.001					
	(0.015)					
Acres_greater_1.55=0 *Megafire buffer damage=1 * Percent buffer burnt	9.941***					
	(0.589)					
Acres_greater_1.55=1 *Megafire buffer damage=0 * Percent buffer burnt	0.025					
	(0.017)					
Acres_greater_1.55=1 *Megafire buffer damage=1 * Percent buffer burnt	26.621**					
	*					
	(1.836)					
		-				
Acres_greater_7.92=0 * Megafire damage=0 * Percent parcel burnt		0.029***				
		(0.007)				
		-				
Acres_greater_7.92=0 * Megafire damage=1 * Percent parcel burnt		4.325***				
		(0.292)				
Acres_greater_7.92=1 * Megafire damage=0 * Percent parcel burnt		-0.011				
		(0.009)				
		-				
Acres_greater_7.92=1 * Megafire damage=1 * Percent parcel burnt		8.907***				
		(0.649)				

	Model A Coeff	Model B Coeff	Model C Coeff	Model D Coeff	Model E Coeff	Model F Coeff
Acres_greater_7.92=0 *Megafire buffer damage=0 * Percent buffer burnt		0.067*** (0.025)				
Acres_greater_7.92=0 *Megafire buffer damage=1 * Percent buffer burnt		8.477*** (0.557)				
Acres_greater_7.92=1 *Megafire buffer damage=0 * Percent buffer burnt		0.021 (0.017)				
Acres_greater_7.92=1 *Megafire buffer damage=1 * Percent buffer burnt		24.685** * (1.791)				
Acres_greater_20.76=0 * Megafire damage=0 * Percent parcel burnt			- 0.023*** (0.007)			
Acres_greater_20.76=0 * Megafire damage=1 * Percent parcel burnt			- 3.839*** (0.281)			
Acres_greater_20.76=1 * Megafire damage=0 * Percent parcel burnt			-0.007 (0.008)			
Acres_greater_20.76=1 * Megafire damage=1 * Percent parcel burnt			- 8.580*** (0.632)			
Acres_greater_20.76=0 *Megafire buffer damage=0 * Percent buffer burnt			0.031** (0.013)			
Acres_greater_20.76=0 *Megafire buffer damage=1 * Percent buffer burnt			7.535*** (0.536)			
Acres_greater_20.76=1 *Megafire buffer damage=0 * Percent buffer burnt			0.024 (0.020)			

	Model A Coeff	Model B Coeff	Model C Coeff	Model D Coeff	Model E Coeff	Model F Coeff
Acres_greater_20.76=1 *Megafire buffer damage=1 * Percent buffer burnt			23.780** * (1.746)			
Acres_greater_53.57=0 * Megafire damage=0 * Percent parcel burnt				-0.014 (0.009) -		
Acres_greater_53.57=0 * Megafire damage=1 * Percent parcel burnt				10.199** * (0.777)		
Acres_greater_53.57=1 * Megafire damage=0 * Percent parcel burnt				-0.009 (0.009)		
Acres_greater_53.57=1 * Megafire damage=1 * Percent parcel burnt				-5.910*** (0.496)		
Acres_greater_53.57=0 *Megafire buffer damage=0 * Percent buffer burnt				0.026 (0.017)		
Acres_greater_53.57=0 *Megafire buffer damage=1 * Percent buffer burnt				23.299** * (1.769)		
Acres_greater_53.57=1 *Megafire buffer damage=0 * Percent buffer burnt				0.021 (0.018)		
Acres_greater_53.57=1 *Megafire buffer damage=1 * Percent buffer burnt				16.505** * (1.361)		
Acres_greater_110.03=0 * Megafire damage=0 * Percent parcel burnt					-0.013 (0.009) -	
Acres_greater_110.03=0 * Megafire damage=1 * Percent parcel burnt					8.135*** (0.634)	
Acres_greater_110.03=1 * Megafire damage=0 * Percent parcel burnt					-0.008	

	Model A Coeff	Model B Coeff	Model C Coeff	Model D Coeff	Model E Coeff	Model F Coeff
					(0.006)	
Acres_greater_110.03=1 * Megafire damage=1 * Percent parcel burnt					-	
					0.529***	
					(0.048)	
Acres_greater_110.03=0 *Megafire buffer damage=0 * Percent buffer burnt					0.025	
					(0.018)	
Acres_greater_110.03=0 *Megafire buffer damage=1 * Percent buffer burnt					22.550**	
					*	
					(1.751)	
Acres_greater_110.03=1 *Megafire buffer damage=0 * Percent buffer burnt					0.019	
					(0.012)	
Acres_greater_110.03=1 *Megafire buffer damage=1 * Percent buffer burnt					1.226***	
					(0.089)	
Acres_greater_95=0 * Megafire damage=0 * Percent parcel burnt						-0.014*
						(0.008)
						-
Acres_greater_95=0 * Megafire damage=1 * Percent parcel burnt						8.210***
						(0.635)
Acres_greater_95=1 * Megafire damage=0 * Percent parcel burnt						0.002
						(0.007)
Acres_greater_95=1 * Megafire damage=1 * Percent parcel burnt						0.062***
						(0.011)
Acres_greater_95=0 *Megafire buffer damage=0 * Percent buffer burnt						0.027
						(0.017)
Acres_greater_95=0 *Megafire buffer damage=1 * Percent buffer burnt						22.759**
						*
						(1.755)

	Model A Coeff	Model B Coeff	Model C Coeff	Model D Coeff	Model E Coeff	Model F Coeff
Acres_greater_95=1 *Megafire buffer damage=0 * Percent buffer burnt						0.006 (0.014)
Acres_greater_95=1 *Megafire buffer damage=1 * Percent buffer burnt						0.237*** (0.013)
Acres_greater_99=0 * Megafire damage=0 * Percent parcel burnt						
Constant	-1.958* (1.110)	-1.961* (1.110)	-1.956* (1.108)	-1.960* (1.110)	-1.959* (1.110)	-1.960* (1.110)
Weibull parameter (P)	1.946	1.948	1.948	1.946	1.946	1.946
var(_cons[County])	0.152*** (0.059)	0.152*** (0.059)	0.152*** (0.059)	0.152*** (0.059)	0.152*** (0.059)	0.152*** (0.059)
AIC	48236.10	48234.91	48221.84	48232.38	48236.80	48233.84
Log likelihood	- 24068.05	- 24067.46	- 24060.92	- -24068.19	- 24068.40	- 24067.92
Observations	96005	96005	96005	96005	96005	96005

Note: Clustered standard errors are in parenthesis. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$

Appendix Table A.2. Robustness Checks for the Interaction of Wildfire and Percent Grassland on the 1000m Buffer

Variables	Coeff
Clay	0.002 (0.005)
silt	-0.001 (0.003)
Kw factor	-0.671 (0.677)
WEI	0.000 (0.001)
Acres	-0.011** (0.004)
Acres^2	0.000*** (0.000)
Class 2	-0.186 (0.133)
Class 3	-0.113 (0.135)
Class 4	-0.132 (0.140)
Class 5	0.101 (0.369)
Class 6	-0.008

Variables	Coeff
	(0.155)
Class 7	-0.060
	(0.195)
Class 2* Acres	0.004
	(0.004)
Class 3* Acres	0.004
	(0.004)
Class 4* Acres	0.005
	(0.004)
Class 5* Acres	0.013
	(0.014)
Class 6* Acres	0.004
	(0.004)
Class 7* Acres	0.007
	(0.005)
T0=2012	1.869***
	(0.076)
T0=2013	1.543***
	(0.071)
T0=2014	1.360***
	(0.070)
T0=2015	1.170***
	(0.089)
T0=2016	1.047***

Variables	Coeff
	(0.093)
T0=2017	0.902***
	(0.095)
T0=2018	0.830***
	(0.058)
T0=2019	0.445***
	(0.095)
Nearest wildfire	-0.000
	(0.000)
Megafire	0.351***
	(0.109)
Megafire *Nearest megafire	-0.000***
	(0.000)
Megafire damage	0.129
	(0.258)
Percent parcel burnt	-0.013
	(0.009)
Megafire damage *Percent parcel burnt	0.016**
	(0.007)
Megafire buffer damage	10.182***
	(0.625)
Percent buffer burnt	0.024
	(0.017)

Variables	Coeff
Megafire buffer damage* Percent buffer burnt	-0.020 (0.017)
Perbuffer50m_crop	-0.005*** (0.001)
Perbuffer50m_developed	-0.000 (0.001)
Perbuffer50m_water	0.010*** (0.003)
Perbuffer50m_grass	0.007*** (0.001)
Land valuation	0.022** (0.009)
Pop estimate	-0.001 (0.000)
2MALag_Crop_index	-0.011*** (0.001)
Mavetemp_10yrlag	0.345*** (0.087)
Maveprep_10yrlag	0.345*** (0.087)
Mavepdsi_10yrlag	-0.016** (0.008)
Megafire buffer damage=0*Perbuffer1000m_grass	0.056

Variables	Coeff
	(0.041)
Megafire buffer damage=1*Perbuffer1000m_grass	0.003***
	(0.001)
Constant	-1.889*
	(1.071)
Weibull parameter (P)	1.948
Variance (constant [County])	0.140***
	(0.054)
AIC	48200.164
Log likelihood	-24050.082
Observations	96005

Note: Clustered standard errors are in parenthesis. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$

Appendix B - Extended Results of the Frequency and Duration

Power Outage Models

Appendix Table B.1 is the results of a linear regression model based on Baarsma and Hop (2009). Looking at the results of duration power outage model, we find that all the attributes of the severe weather power outages apart from time of week had a statistically significant effect on the weighted utility (p value is 0.1 or 0.01). Respondents' preference for backup power services increased with an increase in duration of outage. The value respondents place on backup power services is more when it happens in the evening compared to night-time outages that occur at 10 p.m., followed by an afternoon outage at 10 a.m. and the least being a morning outage at 6 a.m. compared to a night-time outage. The respondents also placed a higher preference for backup power services for an outage that happens in the winter than in the summer. However, the interest in the backup services decreased with the increase in user fees per severe weather outage, as expected. That is, demand for the backup services decreases as user fee increases. For the frequency power outage model, all the coefficients of the model were statistically significant. Preference for backup services increased with frequency of outages and decreased in increase of user fees.

Appendix Table B.1. Estimated Results of the Frequency and Duration Power Outage Models Based on Baarsma and Hop (2009)

	Duration Power Outage Model	Frequency Power Outage Model
	Part A1a	Part A1b
Variables	Utility	Utility
ln Duration	0.474*** (0.010)	
Weekday	-0.054 (0.033)	
24-hour Base category		0.129***

	Duration Power Outage Model	Frequency Power Outage Model
	Part A1a	Part A1b
Variables	Utility	Utility
		(0.030)
ln Frequency		0.136***
		(0.012)
Morning at 6:00 a.m.	0.079*	
	(0.047)	
Afternoon at 10 a.m.	0.086*	
	(0.047)	
Evening at 4 p.m.	0.171***	
	(0.047)	
Winter	0.224***	
	(0.033)	
User Fee	-0.008***	-0.009***
	(0.000)	(0.000)
Constant	-0.823***	0.697***
	(0.050)	(0.025)
Observations	14,088	14,088
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

In the table below, we show the WTP values based on frequency, duration, and both frequency and duration. On average in the Baarsma and Hop (2009) model, respondents willingness to pay was \$3.80 to avoid a four-hour outage, \$44.65 to avoid an eight-hour outage, \$109.38 to avoid a 24-hour outage, \$174.11 to avoid a 72-hour outage, and \$204.20 to avoid a 120-hour outage, see Appendix Table B.2. When we checked the order of WTP based on the average WTP per hour, the order was like that of the RPM. Respondents are WTP more for an 8-hour outage (\$5.58), followed by a 24-hour outage (\$4.56), then a 72-hour outage (\$2.42), then 120-hour outage (\$0.95), and least being a four-hour outage (\$1.87). The least WTP to avoid a 4-hour outage is because 4-hour outage is close to the average D_0 . We also observe marginal WTP peaked at 8 hours of outage and started decreasing afterwards. An upward trend in WTP was observed when frequency of outages increases, as shown in Appendix Table B.2. Respondents on

average are WTP \$16.11 (\$2.01) per event for an outage every 10 years, \$23.60 (\$2.95) per event for an outage every 5 years, \$35.17 (\$4.40) per event for an outage every other year, \$44.65 (\$5.58) per event for one outage per year, \$54.46 (\$6.81) per event for an outage that happens two times per year, and \$64.44 (\$8.06) per event for an outage that happens four times per year and the values in brackets showing average WTP per hour for each of the frequency level.

Appendix Table B.2. WTP Values Per Event for Various Durations and Frequencies Based on Baarsma and Hop (2009) Model

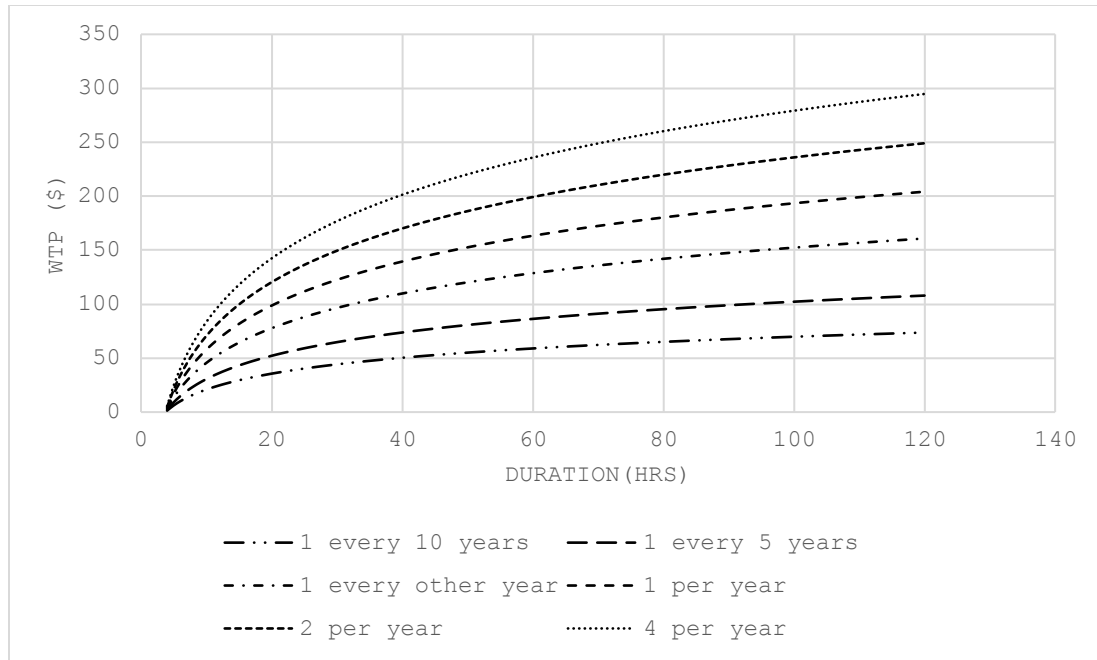
		Difference (RPM-Baarsma and Hop (2009) model)		
Duration of Outage (One per year)	Mean WTP (\$)	Marginal WTP (\$)	Mean WTP (\$)	Marginal WTP (\$)
1 hour	-77.87	-	-10.67	-
4 hours	3.81	1.27	0.01	0.00
8 hours	44.65	10.21	5.35	1.34
24 hours	109.38	4.05	13.82	0.53
72 hours	174.11	1.35	22.29	0.18
120 hours	204.20	0.63	26.22	0.08
Number of outages (of 8 hours)	Mean WTP (\$)	Marginal WTP (\$)	Mean WTP (\$)	Marginal WTP (\$)
1 every 10 years	16.11	-	1.93	-
1 every 5 years	23.60	7.49	2.83	0.90
1 every other year	35.17	3.86	4.22	0.46
1 per year	44.65	1.90	5.35	0.23
2 per year	54.46	0.98	6.53	0.12
4 per year	64.44	0.50	7.73	0.06
Average D0 (hours)		3.75		0.17

In the next paragraphs, we show the WTP results for severe weather power outages for various duration and frequency combinations based on the Baarsma and Hop (2009) model. In the conceptual framework, we talked about the four possible scenarios of frequency and duration combinations. We have excluded Scenario 2 and Scenario 4 because the WTP is zero, see the conceptual section.

Scenario 1: A severe weather power outage of duration $D > D_0$ for a given outage frequency $F > F_0$.

The WTP values for power outages in Scenario 1 are all positive. Figure B.1 shows the estimated WTP values. We see the gap in WTP is largest at a higher frequency and higher duration of outage and a change in frequency has a much more effect on WTP values compared to duration. For example, the WTP is \$ 1.37 per event to avoid a four-hour outage that happens once every 10 years ($F=0.1$) and \$294.75 per event for an outage that happens four times a year for a duration of 120 hours which is approximately 30 times more than the prior. We also observe that at lower durations there is not much difference in WTP at various frequency levels, but the difference becomes pronounced as the duration of outage increases. The WTP graphs for the various frequencies are very steep at duration, less than 20 hours, but it starts to flatten afterwards for lower frequencies, i.e. 1 every 10 years and 1 every five years compared to the other frequencies. It is important to note that although there is a wide gap between WTP values when the outage happens 1 every 5 years and 1 every other year compared to other consecutive frequency levels, this just shows a scaling effect and not a change in preference.

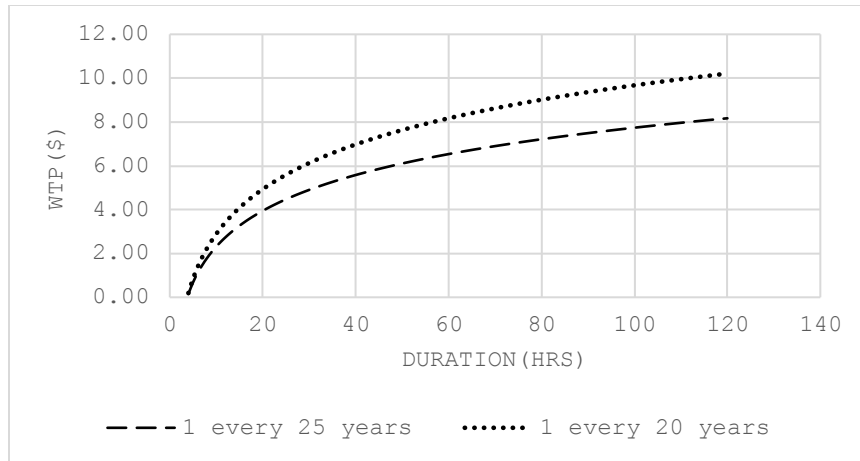
Appendix Figure B.1. WTP Values for Severe Weather Power Outages When $D > D_0$ and $F > F_0$ Based on Baarsma and Hop (2009) Model



Scenario 3: Power Outage of Duration $D > D_0$ for a Given Outage Frequency $F \leq F_0$

The user fee Households are WTP for severe weather power outage of duration $D > D_0$ for a given outage frequency $F \leq F_0$ is positive and not influenced by frequency. Looking at the mean WTP in Figure B.2 we see that the mean WTP is always higher for higher frequency of outages compared to lower frequency. For example, the mean WTP is \$10.21 per event to avoid a 120-hour outage that happens once every 20 years compared to \$8.17 per event to avoid an outage that happens once every 25 years. We also see that there is not much difference in mean WTP at lower frequency of outage. The mean WTP difference to avoid an outage is \$0.04 per event between a four-hour outage that happens every 20 years compared to a four-hour outage that happens every 25 years. See Figure B.2 for the various mean WTP at various duration levels for both frequencies.

Appendix Figure B.2. WTP Values for Severe Weather Power Outages When $D > D_0$ and $F \leq F_0$ Based on Baarsma and Hop (2009) Model



Appendix Table B.3. Estimated Results of Duration Power Outage Model with Household Characteristics and Demographics

Variables	Baarsma and Hop (2009) Part a	Random Parameter Linear Model Part b	
	Weighted Utility	Utility	Standard deviation of Parameter distribution
ln Duration	0.475*** (0.010)	0.510*** (0.011)	0.208*** (0.016)
Weekday	-0.054 (0.034)	-0.058 (0.036)	0.553*** (0.084)
Morning at 6:00 a.m.	0.084* (0.047)	0.072 (0.049)	0.449*** (0.167)
Afternoon at 10 a.m.	0.089* (0.047)	0.095* (0.049)	0.000** (0.000)
Evening at 4 p.m.	0.180*** (0.047)	0.173*** (0.050)	0.544*** (0.143)
Winter	0.229*** (0.033)	0.241*** (0.035)	0.141 (0.311)
User Fee	-0.008*** (0.000)	-0.009*** (0.000)	0.005*** (0.000)
Median Yearly Income	0.000 (0.000)	0.000*** (0.000)	- -
Households Size	0.006 (0.005)	0.048*** (0.010)	- -
House Tenure, Own	-0.114** (0.045)	-0.119 (0.081)	- -
House Tenure, Rented	-0.089 (0.065)	0.007 (0.117)	- -
Years Living in the Area	-0.000	-0.008***	-

Variables	Baarsma and Hop (2009)	Random Parameter Linear Model	
	Part a	Part b	
	Weighted Utility (0.001)	Utility (0.002)	Standard deviation of Parameter distribution
Metropolitan Statistical Area (MSA)	-0.036 (0.041)	0.161** (0.074)	- -
Electric Dependent Sick Households Member	-0.030 (0.042)	0.326*** (0.075)	- -
Backup Energy Source	0.119*** (0.043)	0.345*** (0.077)	- -
Affected by a Power Outage	0.035 (0.034)	0.388*** (0.062)	- -
Constant	-0.813*** (0.074)	3.842*** (0.112)	1.287*** (0.031)
Observations	13,824	13,824	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix Table B.4. Estimated Results for Frequency Power Outage Model with Household Characteristics and Demographics

Variables	Baarsma and Hop (2009)	Random Parameter Linear Model	
	Part A4 a	Part A4 b	
	Weighted Utility	Utility	Standard deviation of Parameter distribution
24-hour Base category	0.130*** (0.031)	0.301*** (0.066)	- -
In Frequency	0.137*** (0.012)	0.151*** (0.013)	0.232*** (0.032)
User Fee	-0.009*** (0.000)	-0.010*** (0.000)	0.008*** (0.000)
Median Yearly Income	-0.000 (0.000)	0.000*** (0.000)	- -
Metropolitan Statistical Area (MSA)	0.043	0.246***	-

Variables	Baarsma and Hop (2009) Part A4 a	Random Parameter Linear Model Part A4 b	
	Weighted Utility (0.038)	Utility (0.082)	Standard deviation of Parameter distribution
Households Size	-0.003 (0.005)	0.027** (0.011)	-
House Tenure, Own	0.069* (0.041)	0.155* (0.090)	-
House Tenure, Rented	0.064 (0.060)	0.183 (0.129)	-
Years Living in the Area	0.001 (0.001)	-0.007*** (0.003)	-
Electric Dependent Sick Households Member	0.018 (0.038)	0.350*** (0.083)	-
Backup Energy Source	-0.115*** (0.039)	-0.010 (0.085)	-
Affected by a Power Outage	-0.053* (0.031)	0.223*** (0.068)	-
Constant	0.689*** (0.056)	5.464*** (0.117)	1.677*** (0.028)
Observations	13,824	13,824	

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix Table B.5. WTP Values Per Event for Various Durations and Frequencies Based on the Models Estimated with Household Characteristic and Demographics

Duration of Outage (One per year)	Baarsma and Hop (2009) Part A5 a		Random Parameter Linear Model Part A5 b		Difference (Part A5 b-Part A5 a)	
	Mean WTP (\$)	Marginal WTP (\$)	Mean WTP (\$)	Marginal WTP (\$)	Mean WTP (\$)	Marginal WTP (\$)
1 hour	-77.33	-	-83.08	-	-5.75	-
4 hours	3.77	1.26	5.69	1.90	1.92	0.64
8 hours	44.33	10.14	50.08	11.10	5.75	0.96
24 hours	108.60	4.02	120.43	4.40	11.83	0.38

72 hours	172.88	1.34	190.78	1.47	17.90	0.13
120 hours	202.76	0.62	223.49	0.68	20.73	0.06
Number of outages (of 8 hours)	Mean WTP (\$)	Marginal WTP (\$)	Mean WTP (\$)	Marginal WTP (\$)	Mean WTP (\$)	Marginal WTP (\$)
1 every 10 years	16.11	-	17.63	-	1.52	-
1 every 5 years	23.60	7.49	25.83	8.20	2.23	0.71
1 every other year	35.16	3.85	38.49	4.22	3.33	0.37
1 per year	44.64	1.90	48.86	2.07	4.22	0.18
2 per year	54.45	0.98	59.60	1.07	5.15	0.09
4 per year	64.43	0.50	70.53	0.55	6.10	0.05

Appendix Table B.6. Mean WTP (\$) Per Event at Various Combination Frequency and Duration Levels Based on Models Estimated with Household Characteristics and Demographics

Frequency								
	1 every 20 years	1 every 25 years	1 every 10 years	1 every 5 years	1 every other year	1 per year	2 per year	4 per year
Duration	Scenari o 2	Scenari o 2	Scenari o 1	Scenari o 1	Scenari o 1	Scenari o 1	Scenari o 1	Scenari o 1
Baarsma and Hop (2009)								
4 hours	0.19	0.15	1.36	1.99	2.97	3.77	4.60	5.45
8 hours	2.22	1.77	16.00	23.43	34.91	44.33	54.07	63.98
24 hours	5.43	4.34	39.19	57.41	85.54	108.60	132.47	156.76
72 hours	8.64	6.92	62.38	91.39	136.16	172.88	210.87	249.53
120 hours	10.14	8.11	73.17	107.19	159.70	202.76	247.32	292.67
RPLM								
4 hours	0.28	0.23	2.05	3.01	4.48	5.69	6.94	8.22
8 hours	2.50	2.00	18.07	26.47	39.44	50.08	61.08	72.28
24 hours	6.02	4.82	43.46	63.66	94.85	120.43	146.89	173.83
72 hours	9.49	7.60	68.52	100.38	149.55	189.88	231.61	274.08
120 hours	11.17	8.94	80.65	118.14	176.02	223.49	272.60	322.58

Appendix C - Models Estimated Using a Single Disaster

Preparedness Information Source

Appendix Table C.1. Ordered Probit Estimation Results for the Perceived Level of Disaster Preparedness (Model A) and for the Perceived Level of Wildfire Preparedness (Model B), Taking into Account Only a Single Disaster Preparedness Information Source.

Variable	<u>Model A</u>	<u>Model B</u>
	Perceived level of disaster preparedness	Perceived level of wildfire preparedness
GP	1.02 (0.68)	-0.24 (0.45)
2018	-0.23** (0.11)	-0.21 (0.15)
2019	0.01 (0.11)	0.17 (0.17)
GP*2018	-0.81 (0.68)	0.66 (0.54)
GP*2019	-1.00 (0.69)	0.00 (.)
Other sources	0.43*** (0.16)	0.36* (0.21)
Other sources*GP	-0.07 (0.59)	-0.42 (1.18)
Television/radio	0.25*** (0.09)	0.38*** (0.14)
Television/radio*GP	0.00 (0.24)	0.01 (0.55)
Internet	0.43*** (0.12)	0.45*** (0.16)
Internet*GP	0.31 (0.39)	-0.48 (1.15)
Print	0.37** (0.15)	0.47** (0.22)
Print*GP	0.03 (0.60)	0.10 (0.92)
Public	1.05*** (0.22)	0.71*** (0.26)
Public*GP	-1.47*** (0.56)	-0.84 (1.14)
Networks	0.61*** (0.18)	0.57** (0.25)

Networks*GP	0.12 (0.53)	-0.13 (0.89)
Exp	0.28*** (0.09)	0.47*** (0.13)
Exp*GP	0.22 (0.24)	0.41 (0.53)
Age	0.01*** (0.00)	0.01** (0.00)
Fem	-0.08 (0.08)	-0.09 (0.13)
Own	0.05 (0.09)	-0.01 (0.15)
Others	-0.28 (0.24)	-0.16 (0.46)
Educ	0.20** (0.09)	-0.10 (0.15)
Moinc	0.00 (0.00)	0.00 (0.00)
White	0.07 (0.10)	0.19 (0.16)
Level (cut) 1 Threshold	-0.38** (0.16)	-0.32 (0.27)
Level (cut) 2 Threshold	0.15 (0.16)	0.20 (0.26)
Level (cut) 3 Threshold	0.77*** (0.16)	0.87*** (0.26)
Level (cut) 4 Threshold	1.25*** (0.16)	1.30*** (0.27)
Log Likelihood	-1113.31	-471.14
Pseudo R ²	0.06	0.06
AIC	2286.63	1000.28
Observations	836	353

Note: Asymptotic standard errors are in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$. Both dependent variables are ordinal variables measuring the perceived likelihood of being prepared for a wildfire (disaster). Level 0 is if the household is not prepared and they do not intend to prepare in the next year. Level 1 is if the household is not prepared but intends to start preparing in the next year. Level 2 is if the household is not prepared but intends to get prepared in the next six months. Level 3 is if the household has been prepared for the last year. Level 4 is if the household has been prepared for more than a year and continues preparing.

Appendix Table C.2. Bivariate Probit Models Estimation Results for Joint Modeling of the Probability of a High Likelihood of a Wildfire Event Occurring and Probability of Having a High Perceived Confidence Level to Prepared for a Disaster (Model A) and the Probability of a High Likelihood of a Wildfire Event Occurring and Probability of Having a High Perceived Confidence Level to Prepared for a Wildfire (Model B) for Entire Study Region, Taking Into Account Only One Source of Information.

Variables	Bivariate Probit Model			
	Model A		Model B	
	Part 1a	Part1b	Part 2a	Part2b
	Estimated probability of a high likelihood of a wildfire event occurring	Estimated probability of having a high perceived confidence level to prepare for a disaster	Estimated probability of a high likelihood of a wildfire event occurring	Estimated probability of having a high perceived confidence level to prepare for a wildfire
GP	-0.06 (0.67)	1.12* (0.65)	-0.68** (0.28)	-0.09 (0.28)
2018	0.24* (0.13)	-0.08 (0.13)	0.30** (0.15)	0.03 (0.14)
2019	0.01 (0.13)	0.01 (0.13)		
GP* 2018	-0.07 (0.67)	-0.61 (0.65)	0.38 (0.30)	0.34 (0.29)
GP* 2019	-0.51 (0.67)	-0.57 (0.64)		
Other sources	0.29 (0.20)	0.33* (0.18)	0.86** (0.43)	0.21 (0.31)
Other sources*GP	0.82 (0.77)	-0.75 (0.72)	0.21 (0.86)	0.21 (0.73)
Television/radio	-0.11 (0.11)	0.32*** (0.11)	-0.26* (0.15)	0.26* (0.15)
Television/radio *GP	0.13 (0.29)	-0.21 (0.28)	0.32 (0.32)	-0.25 (0.31)
Internet	0.17 (0.14)	0.35*** (0.13)	-0.01 (0.20)	0.36* (0.19)
Internet*GP	0.03 (0.44)	-0.05 (0.41)	0.05 (0.47)	-0.33 (0.47)
Print	-0.22 (0.17)	0.09 (0.17)	-0.37 (0.22)	0.04 (0.22)
Print*GP	0.63 (0.61)	-0.86 (0.70)	0.64 (0.66)	0.32 (0.70)
Public	0.68*** (0.26)	0.24 (0.21)	0.83** (0.37)	-0.04 (0.28)

Public*GP	-0.00 (0.75)	-0.25 (0.66)	-0.21 (0.80)	-1.02 (0.89)
Networks	0.29 (0.21)	0.87*** (0.20)	0.19 (0.25)	0.61** (0.24)
Networks*GP	0.25 (0.63)	-0.39 (0.55)	0.28 (0.67)	0.29 (0.62)
Exp	1.00*** (0.11)	0.52*** (0.10)	0.79*** (0.15)	0.39*** (0.14)
Exp*GP	0.21 (0.30)	-0.59** (0.27)	0.46 (0.33)	0.40 (0.30)
Age	-0.01** (0.00)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
Fem	0.19* (0.10)	-0.19** (0.09)	0.10 (0.13)	-0.13 (0.12)
Own	0.12 (0.11)	0.04 (0.11)	0.15 (0.15)	0.19 (0.15)
Others	0.27 (0.31)	0.35 (0.29)	-0.44 (0.44)	0.31 (0.41)
Educ	-0.05 (0.11)	0.19* (0.11)	0.03 (0.14)	0.19 (0.14)
Moinc	-0.00* (0.00)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)
White	-0.05 (0.12)	0.17 (0.12)	-0.22 (0.17)	0.26 (0.18)
Constant	0.11 (0.19)	-1.15*** (0.20)	0.21 (0.26)	-1.27*** (0.26)
Rho (tetrachoric correlation)		0.07 (0.06)		0.17** (0.08)
Log Likelihood		-1003.67		-586.70
AIC		2117.34		1275.40
Observations		836		487

Note: Asymptotic standard errors are in parentheses. *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$.