Rising Wildfire Risk and Private Forest Management Adaptation: Evidence from the Western United States

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Abstract

Wildfire risk has intensified across the western United States, with wildfires generating hundreds of billions of dollars in economic damages each year. Economic theory shows that changing wildfire risk should induce landowners to reduce risk exposure through forest management, though there is little empirical evidence of such landowner adaptation. This study provides the first large-scale empirical evidence on how increasing wildfire risk affects plot-level forest management decisions on non-federal land. Using confidential plot-level data from the U.S.D.A. Forest Service Forest Inventory and Analysis database linked with wildfire perimeters, we examine how nearby wildfires influence decisions regarding planting density and the choice among harvest types on private and state timberland in Oregon, California, and Washington. Controlling for plot and climate factors, we find that increased wildfire exposure leads landowners to lower planting densities and to shift harvest composition toward partial cutting and away from clearcutting, revealing adaptive responses to changing fire risk. A simulation exercise shows how the changing fire regime since 2001 has shifted harvest composition from clearcutting toward partial cutting across non-federal western forests.

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1 Introduction

Large wildfires have become more frequent across the western United States in recent decades, and human-caused climate change accounts for a large share of this increase (Abatzoglou and Williams, 2016). The social costs of this trend are large and growing, with nearly 50 million homes now in the wildland-urban interface (Burke et al., 2021). Recent estimates place the total annual economic cost of wildfire in the United States in the hundreds of billions of dollars (U.S. Congress Joint Economic Committee, 2023), and the mortality costs of wildfire smoke alone are projected to exceed the climate-driven damages from all other causes combined (Qiu et al., 2025). Most economic research on wildfire has focused on two areas. The first is the capitalization of wildfire risk in residential property markets, and the second is the health impacts of wildfire smoke. Far less attention has gone to how fire affects the management of forests themselves. Forests are among the natural resources most exposed to rising fire activity, and the commercially valuable timberland of the western United States is increasingly fire-prone. How private forest landowners respond to a changing fire regime remains largely unknown. Landowner responses to increasing fire risk matters for future forest composition, timber supply, and the many ecosystem services that forests provide.

Long-standing predictions in natural resource economic theory hold that fire risk should shape forest management. Reed (1984) predicts that an increase in fire risk acts like an increase in the discount rate, pushing managers to harvest sooner and lowering land values. When other choice variables are introduced to the Reed formulation, Amacher et al. (2005) predict that landowners facing elevated fire risk should also plant at lower densities and invest in fuel reduction, and Patto and Rosa (2022) show that more frequent fire can move landowners toward partial harvests earlier in the rotation. This work is largely theoretical and numerical, and direct empirical evidence that landowners actually adjust management in response to rising fire risk is scarce. Recent work shows that fire risk is capitalized into western timberland prices, with most of the loss arising from fires on neighboring rather than own land (Wang and Lewis, 2024), but whether that capitalized risk is accompanied by observable changes in how landowners manage their stands is an open question. We study this question in the private and state timberland of Washington, Oregon, and California, a setting with recent large increases in fire risk that allow us to directly test for a management response. Non-federal owners manage primarily for timber revenue, and the region's wide spatial and temporal variation in fire activity provides the variation needed to identify that response.

This paper estimates how rising wildfire activity affects two margins of private forest management. The first is the density at which landowners establish new stands, and the second is the choice among leaving a stand to grow, partial cutting, and clearcutting. We combine confidential plot-level data from the U.S. Forest Service Forest Inventory and Analysis (FIA) program with wildfire perimeters from the Monitoring Trends in Burn Severity (MTBS) database and climate data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM). The confidential FIA data are essential to our design, because publicly available plot locations are obscured in ways that introduce measurement error into any measure of fire activity near a plot. Using true plot locations, we construct measures of localized and regional fire exposure around each plot, and we relate these measures to planting density in a model that controls for unobserved heterogeneity through county and planting-year fixed effects. We relate the same measures to the annual harvest choice with a multinomial logit model that uses a correlated random effects specification to control for time-invariant plot heterogeneity (Train, 2009; Mundlak, 1978). This harvest model is designed to test for substitution between partial cutting and clearcutting in response to fire.

Our results indicate that landowners adapt management along both margins. Planting density falls as recent nearby fire activity rises, and the response is driven by changes in fire activity over time near a plot. On the harvest margin, elevated fire activity shifts landowners toward partial cutting and away from clearcutting. A formal test rejects the hypothesis that fire affects the two harvest types equally, which gives evidence in line with landowners shifting toward partial cutting. This substitution is driven by regional fire activity around the plot.

In contrast, we find no evidence that landowners increase pre-commercial thinning, a costly fuel-reduction activity that generates no immediate revenue.

This paper makes several contributions. First, it provides the first large-scale empirical evidence that private forest landowners adapt management to rising fire risk, broadly in the direction that natural resource economic theory predicts. Amacher et al. (2005) model how fire risk shapes planting density, pre-commercial thinning, and the timing of clearcut harvest, predicting that as risk rises landowners plant less densely, thin more, and extend rotations, and we test these predictions directly with observed management decisions. Second, the paper complements recent evidence that fire risk is capitalized into timberland prices (Wang and Lewis, 2024) by identifying the behavioral channel that accompanies that capitalization, showing that the same proximate fire activity that lowers land values also reshapes management. Third, the paper extends a growing body of empirical work on forest adaptation to climate, which has examined responses to climate means and weather variability (Hashida and Lewis, 2019; Johnson and Lewis, 2024), to the case of disturbance risk from wildfire in the western United States. A related literature estimates the costs of future wildfire, smoke, and climate change (Qiu et al., 2025), but does not account for forest management adaptation as risk rises. Finally, our results speak to the design of fuel-treatment policy. Landowners increase partial cutting on their own, a revenue-generating activity, but do not increase pre-commercial thinning, a pure cost. This suggests that cost-sharing programs are most valuable when directed at fuel-reduction activities that landowners will not undertake on their own, consistent with the role for cost-sharing identified in theoretical work on fire prevention (Amacher et al., 2005). The composition of management also matters for fire outcomes in its own right, as homogeneous plantations burn more severely than structurally diverse stands (Zald and Dunn, 2018). Therefore, the adaptation we document is consistent with landowners lowering their perceived risk exposure.

The remainder of the paper is organized as follows. Section 2 describes the context of forestry and wildfire in the western United States. Section 3 presents the theoretical framework. Section 4 describes the data. Section 5 outlines the empirical strategy. Section 6 presents the results. Section 7 discusses their implications and concludes.

2 Study Context

The Pacific states of Washington, Oregon, and California contain some of the most productive timberland in the world. A mild, wet climate supports rapid growth of the commercially valuable Douglas-fir across the region. These forests are also increasingly exposed to wildfire. Large wildfires have become substantially more frequent across the western United States in recent decades, driven in large part by a warmer and drier climate (Abatzoglou and Williams, 2016). Figure 1 illustrates the scale of this change within our study region. The total area burned across the three states more than doubled between the 1984–2003 and 2004–2023 periods, with the increase concentrated in the drier interior.

This recent and pronounced increase in fire activity makes the region an appropriate setting for our research question. Natural resource economic theory has long held that fire risk should be capitalized into land values and should shape management decisions (Reed, 1984; Amacher et al., 2005). In a high-fire environment where the fire regime is stable, however, that risk is already embedded in expectations and in observed management, and we would not expect to see changes in management activity unless risk expectations themselves change. It is the change in fire risk that creates the variation needed to study adaptation. As nearby fire activity rises, landowners update their beliefs about the risk facing their own stands. The temporal and spatial variation in fire activity documented in Figure 1 therefore provides the setting in which long-standing theoretical predictions about management under fire risk can be brought to observed decisions.

Forest land in the region is a mosaic of federal and non-federal ownership, shown in Figure 2. Federal forest is concentrated in the Cascades, Sierra Nevada, Klamath, Blue Mountains, and Olympic ranges, while private and state lands are interspersed throughout, most extensively in the Oregon Coast Range, western Washington, and northern California. Non-federal owners hold a smaller share of the forested landscape than federal owners, but private lands still make up a large portion of the landscape and are concentrated on the most productive sites. This contrasts with the southeastern United States, where forest land is predominantly private but has not experienced the scale of recent wildfire activity seen in the West. We restrict our analysis to private and state timberland because non-federal owners manage primarily for timber revenue, so their decisions are the ones standard profit-maximizing economic theory describes. The forests in our sample span a range of species and include both planted and naturally regenerated stands. Figures 6 and 7 in the appendix display the composition of our estimating sample by forest type group and by stand origin. Planted stands, which are most common in the more actively managed timberland of Washington and Oregon, are the relevant population for the planting-density margin we study, while the harvest-choice analysis draws on the broader set of stands.

There are a range of relevant management activities on managed timberland, which the following section formalizes and which we briefly describe here. A common decision for a timberland owner is when and how to harvest the stand. A clearcut harvest removes essentially all merchantable timber, after which the stand is replanted to begin a new rotation. In choosing to clearcut and replant, the landowner decides both when to harvest and how densely to establish the new stand. While clearcutting is the most common harvesting choice on many productive timberland sites, a landowner may instead undertake a partial cut, often referred to as a commercial thinning, in which a portion of the merchantable volume is harvested and sold while a residual stand is retained. Both clearcuts and partial cuts generate revenue. The two differ in the stand structure they leave behind, and the more heterogeneous structure produced by a partial cut is believed to burn less severely than the dense, even-aged structure of a clearcut-and-replant (Zald and Dunn, 2018).

A landowner may also undertake pre-commercial thinning, in which excess growing stock is cut but not removed for sale. Unlike clearcuts and partial cuts, pre-commercial thinning generates no immediate revenue and incurs a cost. However, pre-commercial thins can improve the future growth of the stand and may reduce future fire risk. Finally, prescribed burning is another activity by which landowners could influence the fire risk and severity on their stands. Prescribed burning is currently uncommon on private timberland in the western United States, owing to liability concerns, drier conditions, and landowner risk perceptions (Miller et al., 2020), and is more common on public lands. This again contrasts with the southeastern United States, where most prescribed burning takes place on private land. We do not examine prescribed burning in this analysis.

3 Forest Management Under Wildfire Risk: A Theoretical Framework

3.1 Fire risk, stand structure, and the value of forestland

We consider a risk-neutral, non-federal forest landowner who chooses management to maximize the expected present value of net returns to the land (Faustmann, 1849; Guo and Costello, 2013). The landowner discounts future returns at a constant rate r, with discount factor $\delta = e^{-r}$. A stand of age a produces standing timber volume $Y(a, D)$, where D is the density (trees per acre) at which the stand was established, with $Y_a > 0$ and $Y_D > 0$. Assume timber sells at a constant stumpage price p. Fire arrives as a Poisson process with arrival rate

$$\lambda = \lambda(s, x), \tag{1}$$

where s denotes the stand's own structure and x collects the exogenous landscape determinants of fire hazard, including climate, terrain, and surrounding fuels. The landowner takes x as given, but influences the structural component s through management. Through s, management affects fire outcomes in two ways. First, it moves the arrival rate λ, since the structure left in place changes how readily the stand burns. Second, it moves the share of standing value that is lost when a fire occurs. Let $\varphi \in [0, 1]$ be the salvage fraction, the share of standing timber value that is recovered after a fire conditional on a fire occurring. A landowner who engages in a given management activity can influence φ by altering the structure of the stand, so that the same fire destroys more or less of the standing value depending on how the stand was managed. We make no claim about the direction in which a given management action moves either λ or φ. Reed (1984) shows that when fire is a constant-hazard catastrophic event that destroys the entire standing stock, the optimal-rotation problem is equivalent to a no-fire problem in which the discount rate is raised from r to $r + \lambda$. We adopt a standard generalization in which loss need not be total (Amacher et al., 2005; Patto and Rosa, 2022). Conditional on a fire, a fraction $(1 - \varphi)$ of standing timber value is destroyed and a fraction φ is recovered through salvage. Because management moves both λ and φ, each is specific to the management regime the owner chooses. The value of holding a stand under regime j going forward is discounted at the fire-adjusted effective rate $r + \lambda_j(1 - \varphi_j)$, the ordinary rate plus the arrival rate scaled by the loss given fire. Each management action commits the owner to a stand structure s_j, an arrival rate $\lambda_j = \lambda(s_j, x)$ and salvage fraction $\varphi_j = \varphi(s_j)$. Doing nothing retains the existing dense, even-aged stand, with $\lambda_{\text{none}} = \lambda(s_{\text{none}}, x)$ and φ_{none}. A partial cut retains a lower-density, heterogeneous residual, with $\lambda_{\text{partial}} = \lambda(s_{\text{partial}}, x)$ and φ_{partial}. A clearcut replaces the stand with a new even-aged plantation established at density D, such that $\lambda_{\text{clear}} = \lambda(s_{\text{clear}}(D), x)$ and $\varphi_{\text{clear}} = \varphi(s_{\text{clear}}(D))$. We assume two relationships hold for the salvage fraction. First, among planted stands, the salvage fraction is decreasing in planting density,

$$\varphi'(D) < 0, \tag{2}$$

an assumption consistent with the fire-ecology evidence that denser plantings produce more continuous fuels and a more severe burn (Zald and Dunn, 2018). Second, among the structures left in place by a harvest decision, the heterogeneous residual of a partial cut survives fire better than either a dense unharvested stand or a newly established even-aged plantation,

$$\varphi_{\text{partial}} > \varphi_{\text{clear}} \approx \varphi_{\text{none}}, \tag{3}$$

The landowner's problem can be written as a single stand value function. A stand is described by its age a and establishment density D, so that two stands of the same age but different density need not have the same value $V(a, D)$. Each period, the owner of a stand (a, D) chooses the action with the highest value among doing nothing, partial cutting, and clearcutting,

$$V(a,D) = \max \begin{cases} \delta\, \mathbb{E}\big[V(a+1, D)\big] & \text{(no harvest)} \\[2ex] R_{\text{partial}}(a,D) + \delta\, \mathbb{E}\big[V'_{\text{partial}}\big] & \text{(partial cut)} \\[2ex] R_{\text{clear}}(a,D) + \max\limits_{D'}\ \delta\, \mathbb{E}\big[V'_{\text{clear}}(D')\big] & \text{(clearcut and replant)} \end{cases} \tag{4}$$

where $R_{\text{partial}}(a, D)$ and $R_{\text{clear}}(a, D)$ are the immediate net revenues from partial and clearcut harvests. Doing nothing retains the existing dense, even-aged stand, which carries $(\lambda_{\text{none}}, \varphi_{\text{none}})$. A partial cut realizes revenue on the harvested portion and retains a heterogeneous residual that carries $(\lambda_{\text{partial}}, \varphi_{\text{partial}})$. A clearcut realizes the full standing value and replants a new even-aged stand at a newly chosen density D', which carries $(\lambda_{\text{clear}}(D'), \varphi_{\text{clear}}(D'))$. The landowner thus chooses the management action and, in the case of a clearcut, the replanting density D' to maximize expected net returns.

We do not observe the hazard λ or its exogenous component x directly. In the empirical analysis, we proxy a rise in landscape fire hazard with recent fire activity in the area surrounding the plot, the *Fire* measures described in Section 4. The comparative statics below are stated in terms of an increase in x.

3.2 When fire risk rises, landowners move toward fire-resilient stand structures

In this section we trace how a rise in fire risk affects each of the two management margins. An increase in the exogenous hazard x raises every stand's arrival rate $\lambda_j(s, x)$ and thereby the effective rate $r + \lambda_j(1 - \varphi_j)$. The value of holding any given stand therefore falls as fire risk rises,

$$\frac{\partial V}{\partial x} < 0. \tag{5}$$

Because the landowner's choices determine the stand held going forward, rising fire risk moves each decision toward the more fire-resilient option.

At a clearcut-and-replant, the landowner chooses planting density D, which determines timber volume $Y(a, D)$, salvage fraction $\varphi(D)$, and arrival rate $\lambda(D)$. The optimal density equates the marginal benefit and marginal cost of an additional tree. A higher density raises expected timber volume, since $Y_D > 0$, but lowers the salvage fraction, since $\varphi'(D) < 0$, which reduces the value retained when a fire occurs. A rise in the exogenous hazard x raises the arrival rate and thus increases the weight placed on this salvage loss. The marginal cost of density therefore rises relative to its marginal benefit, and the landowner optimally establishes the stand at a lower density,

$$\frac{\partial D^*}{\partial x} < 0. \tag{6}$$

If we further assume that denser, more continuous fuels carry fire more readily,

$$\lambda'(D) \geq 0, \tag{7}$$

(Zald and Dunn, 2018), the arrival rate gives a second reason to plant less densely as fire risk rises.

The same logic extends to the choice among the three harvest actions. Each action leaves the owner with a different stand with a different value function carrying its own arrival rate and salvage fraction. A rise in fire risk lowers all three values, but by different amounts, and the action whose value falls least becomes relatively more attractive. Because the partial-cut residual carries the highest salvage fraction by (3), its value falls least through this channel, which favors partial cutting over both inaction and clearcutting. The model does not sign the comparison between partial cutting and clearcutting on its own, since clearcutting realizes the standing value immediately while partial cutting leaves merchantable timber exposed. We therefore treat the direction of the harvest-composition response as a hypothesis motivated by the model and test it in the data.

3.3 Empirical predictions from the model

The framework gives two predictions that guide the empirical analysis. First, an increase in fire risk lowers the density at which landowners establish new stands. Second, an increase in fire risk changes the relative attractiveness of harvest types, shifting harvest composition toward partial cutting. Both reflect the same behavior, a move toward more fire-resilient stands as fire risk rises, observed at two separate margins. We describe the methods used to test both predictions in Section 5.

4 Data

4.1 Forest Management Data

We are interested in the effect of wildfire occurrence on subsequent forest management decisions. We observe a suite of forest management decisions and forestry data from the USDA USFS Forest Inventory and Analysis program (FIA). The FIA is a national survey of permanent forest plots across the United States. The FIA uses a stratified random sampling approach, and samples repeated plots across the US across all ownership groups. In this paper, we restrict to private and state forest plots, whose revenue focussed management objectives are most in line with our economic theory of forest management decisions under changing fire risk. Publicly owned forests have a wide range of management objectives apart from revenue maximization (U.S. Congress, 1960; Loomis, 2002), and are thus excluded from this study. Our study period begins in 2001, corresponding with the current inventory design of the FIA (Bechtold and Patterson, 2005). FIA plots in the West are measured on 10-year remeasurement cycles, meaning that, on average, a plot will be re-measured once every 10 years, and all plots will be measured within 10 years. FIA plots are standardized to be one acre. Plots are also delineated into forest "conditions", which are defined as areas within the plot with similar topography, forest types, or ownership (Bechtold and Patterson, 2005). A given FIA plot can have one or multiple conditions. Our unit of analysis is the FIA condition, which we refer to interchangably as a FIA plot throughout this paper.

For each FIA condition on a given plot, we observe a number of management decisions and forest characteristics. The forest characteristics include the age of the forest stand, the forest type, whether the stand was planted or naturally regenerated, and topographic information about the condition. We also observe a set of management activity and disturbance indicators. FIA field crews record whether a condition has been clearcut, partial cut, or pre-commercially thinned, along with the estimated year of each activity. The FIA classifies a harvest as a clearcut when essentially all merchantable trees have been removed, and as a partial cut when a portion of the merchantable volume has been removed while a residual stand of commercially desirable trees is retained. Partial cuts encompass a range of silvicultural practices, including commercial thinning operations in which a portion of the standing volume is harvested for revenue while stand density is reduced. Unlike clearcuts, partial cuts retain a residual stand that continues to grow and may be entered again in future harvest cycles. Both clearcuts and partial cuts generate revenue for the landowner. The FIA also records pre-commercial thinning, in which excess growing stock is cut but not removed for sale, making it a costly fuel-management activity rather than a revenue-generating harvest. We restrict our main analysis to the choice across clearcut, partial cut, and no action, and we report results on pre-commercial thinning in Appendix C.5.

The FIA also records detailed disturbance information on each plot, such as whether the plot experienced a crown or ground fire, insect outbreak, or wind damage. For each of these recorded disturbances, we observe the estimated year of the disturbance. We drop from our sample any harvest field-coded as a salvage harvest, since these are responses to a destructive event rather than the adaptation decisions our model describes. Taken together, the FIA data allow us to compile a rich dataset of non-federal forest plots measured between 2001 and 2024 in Oregon, California, and Washington, which we link to a broad suite of nearby fire indicators. To do this, we use confidential FIA plot-level data. The FIA program is a publicly available dataset. However, to preserve landowner confidentiality, the FIA program perturbs plot location coordinates by up to roughly 1 km (Bechtold and Patterson, 2005). The coordinates of a small fraction of plots on private land are also swapped with those of similar forest plots within the same county (Bechtold and Patterson, 2005; McRoberts et al., 2005). Because we are interested in management responses to nearby fire activity, this fuzzing and swapping could introduce measurement error when linking plots to fire occurrences. To overcome this, we use confidential plot-level data with the true plot locations, which we link to nearby fire activity.

4.2 Wildfire Data

Given we are interested in the effect of wildfire on subsequent forest management decisions, we need to link our FIA plot data to a broad suite of fire information. To do this, we utilize the Monitoring Trends in Burn Severity (MTBS) dataset. The MTBS contains detailed information on all large U.S. wildfires (Eidenshink et al., 2007). In the Western U.S., we observe all fires greater than 1,000 acres. For each fire, we observe its final perimeter and ignition date. We then use this information and link fire activity to our FIA plot data. For each FIA plot in our sample, we construct a number of fire activity and intensity measures, linking each fire variable to each management decision. For each FIA plot, we create numerous spatial buffers, and observe the amount of fires over time, the acreage burned, and the change in fire activity over time. Each fire variable is constructed to measure fire activity that occurred prior to each observed management decision. We construct each of these variables over 5, 10, and 15 year time horizons.

Figure 4 depicts the general intuition of our fire variable construction. For a management activity observed on FIA plot i in year t, we construct a number of fire metrics that capture fire activity surrounding plot i prior to year t. For example, for a given plot with a clearcut harvest in 2017, we observe the amount of fires surrounding that plot over various spatial distances, in the 5, 10, and 15 years prior to 2017. This allows us to directly test how management decisions respond to past fire exposure at the plot level. Beyond the level of fire activity, we also measure how local fire activity is *changing* over time by differencing fire exposure across successive look-back windows; Figure 5 illustrates the construction of these change (Δ) variables. For a detailed description of our fire variable construction and the full variable list, see Appendix A.1.

4.3 Climate Data

Climate variables may be correlated with both timber productivity and wildfire intensity (Restaino et al., 2016; Zhuang et al., 2021; Abatzoglou and Williams, 2016). To observe climate information in our setting, we use the Parameter-elevation Regressions on Independent Slopes Model (PRISM) dataset. The PRISM group gathers weather observations from a wide range of monitoring networks across the U.S. and applies sophisticated quality control measures and mapping methods to develop spatial climate datasets at varying spatial scales (Daly et al., 2008). We use the PRISM data at a 4 km scale. For each FIA plot we construct a suite of historical climate info, at 15 and 30 year time scales relative to the observed management year. For example, for a plot with a management activity in 2013, we observe a set of climate information for that plot, downscaled at a 4 km level, averaged over the 15 and 30 years prior to the management year. We construct both annual and growing season (April-July) climate variables.

4.4 Summary Statistics

Tables 1 and 2 report summary statistics for the two estimating samples used in our empirical analysis: a pooled cross-section of recently planted conditions used to estimate planting density, and an annual condition-year panel used to estimate harvest choices. The two samples differ in their unit of observation, size and temporal structure, so we summarize them separately.

In our planting density estimating sample, we observe 556 recently planted forested conditions planted between 2004 and 2023, corresponding to 530 unique FIA plots. The majority of these planted stands are in Washington and Oregon, as these states have more actively managed, and thus planted, timberland than California, a region with more naturally regenerated forest stands. The most common type of planted species in our sample is the commercially viable Douglas-Fir, with an average trees per acre (TPA) of 309. We observe TPA at the time of FIA measurement, which may be different than the planting TPA chosen by the land manager due to natural regeneration and mortality. However, the average time between planting and FIA measurement in our sample is short (3.9 years).

In Table 1, we also report summary statistics for the fire variables used in the main specification in our planting density models. For each recently planted stand, we observe the change in fire activity surrounding that plot within 30 km as well as the levels, lagged to be strictly pre-planting and span the 10 years before planting. For example, for a stand planted in 2012, we observe the number of fires that occurred within 30 km of that plot between 2002-2011. We also observe the change in the number of fires around that plot over time. For a stand planted in 2012, this is measured as the difference between the number of fires around that plot between 2002-2011 and between 1992-2001. If 3 fires occurred between 2002-2011, and 2 fires occurred between 1992-2001, the value of this variable would equal 1, the difference between the two. Positive values of this variable indicate that a given plot had increased fire activity in the recent time window and is meant to capture changing risk perceptions for the landowner. The average amount of fires that occurred within 30 km of our observed planted plots in the 10 years prior to the planting year is 1.24, and the 10 year change in fire counts is 0.50, meaning that on average plots had more fire activity in the 10 years prior to planting than the 10 years before that. We report fire information in different spatial buffers, from 0-5km and 5-30km away. We also observe if a stand was planted following a direct burn. These are likely scenarios in which a stand was destroyed by fire and a subsequent replanting decision occurred. In our estimating sample, 7.2% of recently planted stands were planted after a direct burn.

In Table 2, we report summary statistics for our harvest choice models estimating sample. This sample consists of forested FIA conditions and plots in Oregon, California, and Washington measured between 2001 and 2024. Given that normal harvesting decisions typically occur on older stands, we restrict our sample to plots with stand ages of 30 and older. We also drop any plots that were directly burned with a subsequent harvest marked as salvage, a management code determined by FIA field crews. In this estimating sample, we observe 5,277 unique forested conditions belonging to 4,367 unique FIA plots measured between 2001-2024, giving us an annual panel of 51,451 condition-year observations. Conditions enter the sample at their first FIA measurement, and leave the sample at their final FIA measurement, or at the time of a clearcut harvest, whichever occurs first. In each of our harvest choice models, we include a stand age control, capturing the age of a given stand in a given year. However, we only observe this variable at the time of a given FIA measurement. To construct an annual panel for FIA conditions, we infer this stand age variable in between FIA measurements. This is possible because we observe any management decision that would reset the stand age, as well as the timing of such a decision. For example, for a given plot measured in 2004 and 2014, we directly observe the age of the stand in 2004 and 2014, and infer the age in between measurements. If the stand was 40 years old in 2004 and 50 years old in 2014, we can infer an age of 41 in 2005, and so on. We also know if a given stand was clearcut in between measurements, which would reset the stand age and that stand would also be dropped from the sample at the time of the clearcut. We also include annual time varying controls in our harvest choice models from other data sources that do not need this annual inference. We control for plot level annual climate exposure from PRISM, and construct our annual fire exposure metrics which do not rely on FIA measurements. This annual panel approach results in 51,451 unique condition year observations between 2001 and 2024.

In our harvest choice sample, we observe plots throughout Oregon, California, and Washington, with slightly more observations in Oregon and Washington. Given the annual condition-year sample design, the majority of condition years do not have a management action take place, about 97.89% of condition years do not contain a management action. Of the remaining condition years for which we do observe a harvest activity take place, 0.86% contain partial cuts and 1.24% contain clearcuts. In any given year, a harvest action is rare given the passive nature of forest management in the Western United States. In Table 2, we also provide summary statistics of the fire variables used in our main harvest choice model specifications. On average, plots contained about 4 fires within 30 km during a 15 year window, with about 30,000 acres burned. Notice that this average fire count is higher than our stand density estimating sample, which is driven both by the longer time window as well as the fact that actively managed planted stands are situated in less fire prone environments, as supported by the warmer and drier climate variables in Table 2 compared to Table 1. On average, conditions in our harvest choice estimating sample have a stand age of 74.7 years.

5 Empirical Strategy

5.1 Planting Density

To estimate the effect of fire on planting-density decisions, we relate the density at which a stand is established to the fire activity that preceded it. For a stand i established in year t, we estimate the reduced-form planting-density equation

$$\ln TPA_{it} \;=\; \beta_0 \;+\; \beta_1\, Fire_{it} \;+\; \beta_2\, Burn_{it} \;+\; \beta_3\, Climate_{it} \;+\; \beta_4\, X_{it} \;+\; \mu_{c(i)} \;+\; \tau_t \;+\; \varepsilon_{it}, \tag{8}$$

where the dependent variable $\ln TPA_{it}$ is the log of planted trees per acre of the dominant species, our measure of planting density. $Fire_{it}$ is a vector of wildfire-exposure measures recorded over a window ending the year before planting, the count of fires, acres burned, or their decade-over-decade change, entered either as a single 0–30 km aggregate or as 0–5 and 5–30 km rings. $Burn_{it}$ is a dummy variable equal to one when stand i itself burned before it was planted. $Climate_{it}$ is a vector of fifteen-year growing-season climate normals (maximum vapor pressure deficit, precipitation, and mean temperature). X_{it} denotes a vector of stand controls that account for land attributes such as elevation, slope, aspect, and site class, along with stand age and time since planting; the topographic attributes are fixed for a stand, while stand age and time since planting are specific to the year of measurement. We use c to index counties, and thus $\mu_{c(i)}$ represents county fixed effects. Planting-year fixed effects are captured by τ_t, and ε_{it} is an idiosyncratic error term. Prediction 1 corresponds to a negative coefficient on wildfire exposure. We estimate equation (8) by OLS on the pooled cross-section, weighting each stand by its condition size, with standard errors clustered by county. With county and planting-year fixed effects, the fire coefficient is identified from variation in pre-planting fire activity across stands established in the same year and within the same county. Our identifying assumption is that, conditional on this fixed-effect structure and the climate and stand controls, the timing and location of nearby fire are unrelated to other determinants of planting density. Under this assumption, β_1 recovers the causal effect of fire exposure on the density at which landowners establish new stands.

5.2 Harvest Choice

To estimate the effect of fire on harvest decisions, we model the harvest margin as an annual discrete choice. The landowner managing condition i in year t selects the action j among doing nothing, partially cutting, and clearcutting that maximizes the latent value $U_{ijt} = V_{ijt} + \varepsilon_{ijt}$, where ε_{ijt} is an i.i.d. Type-I extreme value error, which yields a multinomial logit (Train, 2009). Normalizing the value of doing nothing to zero, the value of each active alternative $j \in \{\text{partial, clear}\}$ is

$$V_{ijt} \;=\; \alpha_j \;+\; \beta_j\, \mathit{Fire}_{it} \;+\; \xi_j\, \overline{\mathit{Fire}}_i \;+\; \gamma_j\, Z_{it} \;+\; \psi_j\, \overline{Z}_i \;+\; \tau_{jt}, \tag{9}$$

so that the probability that condition i receives action j in year t is

$$\Pr(y_{it} = j) \;=\; \frac{\exp(V_{ijt})}{\sum_k \exp(V_{ikt})}, \qquad V_{i,\,\text{none},\,t} = 0, \tag{10}$$

where y_{it} is the management action on condition i in year t, doing nothing is the base outcome, and k runs over the three actions. Fire_{it} is the same vector of wildfire-exposure measures as above, here accumulated over the fifteen years before year t, and Z_{it} is a vector of time-varying controls: stand age, the fifteen-year growing-season climate normals, and a direct-burn dummy equal to one if the condition burned in either of the two prior years. Because each condition is observed repeatedly over time, we follow a correlated random effects approach and include the within-condition time averages $\overline{\mathit{Fire}}_i$ and $\overline{Z}_i$, which absorb correlation between the condition's time-invariant unobservables and the regressors (Mundlak, 1978). The constants α_j and the coefficients β_j, ξ_j, γ_j, and ψ_j are specific to each action, and τ_{jt} are action-specific period fixed effects. We estimate equation (10) by maximum likelihood, weighting each condition–year by its condition size, with standard errors clustered by plot. The correlated random effects terms absorb the condition's time-invariant unobservables, so the fire coefficients are identified from within-condition variation in fire activity over time.

Our identifying assumption is that, conditional on these terms and the time-varying controls, year-to-year changes in nearby fire are unrelated to other time-varying determinants of the harvest decision. Prediction 2 concerns the composition of harvests rather than their overall frequency, and has two parts. First, the fire coefficient in the partial-cut equation is positive, $\beta_{\text{partial}} > 0$. Second, fire shifts landowners between the two harvest types, which we test as

$$H_0\colon\ \beta_{\text{partial}} = \beta_{\text{clear}}, \tag{11}$$

using a Wald test. A rejection of (11) indicates that fire reallocates harvests across types rather than scaling them equally, consistent with substitution toward partial cutting.

6 Results

6.1 Planting Density Models

In Table 3, we present our results for the planting density model. We are interested in the effect of wildfire exposure on planting density decisions. In column 1, we measure wildfire as the change in nearby wildfire counts over time. Specifically, we measure the count of wildfires within 30 km of the FIA plot, taking the difference in fire activity between the 10 years prior to the planting decision, and the 10 years prior to that. This wildfire difference measure is meant to control for changing risk perceptions over time. If this variable is positive, it indicates that an FIA plot had more fires within 30 km in the last 10 years compared to the 10 years before that. In column 2, we present results for the raw count of wildfires within 30 km in the 15 years prior to planting. In column 3, we present results for the total acreage burned within 30 km in the 15 years prior to planting. In columns 4, 5, and 6, we decompose each of these three measures into 0-5 km and 5-30 km bins to test for diminishing planting density responses across space. In each of these specifications, we include a control indicating whether the planting decision occurred after the FIA forest condition was directly burned.

This allows us to test for different landowner responses to direct burns vs. regional fire activity. Additionally, this controls for differences in forest site quality, as directly burned plots may be less productive and able to maintain less trees per acre. Additionally, plots that were directly burned between the planting year and FIA measurement year are dropped. We also include a time since planting indicator, measured in years. This controls for potential mortality effects and natural regeneration, as our dependent variable is observed at the time of FIA measurement, not at the time of planting. Additionally, we control for the age of the stand at FIA measurement. Time since planting and FIA stand age should coincide on fully clearcut-and-replanted plots, but in practice they differ because FIA stand age is the average total age of trees in the field-recorded stand-size class, which can incorporate leftover residuals or regeneration that do not reflect the planting date. For this reason, we include both controls: time since planting indexes the management event, while stand age captures the realized dominant age structure. Our results are robust to including and excluding both of these age controls (Appendix B.1, Table 8). Each specification in Table 3 also includes forest site class dummies to control for differences in land productivity, topographic such as elevation and slope, climate controls which may be correlated both with timber productivity and wildfire activity (Restaino et al., 2016; Zhuang et al., 2021; Abatzoglou and Williams, 2016), as well as county and planting year fixed effects.

The outcome of interest in Table 3 is the recorded trees per acre of the dominant species on a given FIA condition at the time of plot measurement. We do not observe trees per acre on a forest stand at the time of planting, but instead the trees per acre at the time of measurement, which on average comes between 1-10 years after planting given 10-year FIA remeasurement cycles in the West. Recorded trees per acre at measurement may differ from the true planting density choice for two main reasons: natural regeneration and mortality. We aim to get rid of these concerns in two main ways. First, we control for the time since planting, which can capture some natural regeneration and mortality effects that occur over time after stand establishment. Additionally, our trees per acre outcome variable specifically counts the number of trees that belong to the dominant species on the condition, as recorded by FIA field crews. For example, a planted Douglas-Fir stand in the western United States may contain 350 planted Douglas-Fir trees per acre, but an additional 200 trees per acre of hardwoods and other naturally regenerating tree species. In this example, we observe the number of Douglas-Fir trees per acre as our dependent variable. Additionally, the FIA breaks up tree classifications into seedlings and trees, where seedlings transition to trees once they pass a size threshold. Our trees per acre measure counts both seedlings and trees, and our results are not sensitive to different specifications (Appendix B.1, Table 8). We cluster our standard errors at the county level.

In Table 3 column 1, we estimate a negative and statistically significant effect of wildfire activity on planting density. Specifically, having an additional fire within 30 km in the last 10 years compared to the 10 years prior is associated with a 9.4% reduction in TPA. A one standard deviation increase in fire count within the buffer (1.79 additional fires) is associated with a 16.2% reduction in planting TPA. Applied to the sample mean of approximately 309 trees per acre for Douglas-fir, this corresponds to roughly 50 fewer trees per acre. In column 2, we control for the number of fires within 30 km of a plot in the 15 years prior to planting. We estimate negative but not statistically significant effects of this measure as well, although the effect is much smaller in magnitude than our estimated coefficient in column 1. In column 3, we control for the total acreage burned within 30 km in the 15 years prior to planting. We estimate a small positive effect of this measure, but it is also not statistically significant.

In columns 4, 5, and 6, we investigate whether the fire effect on planting density operates primarily through proximate or more distant fire activity. To do this, we decompose the 0-30 km buffer into an inner ring (0-5 km) and an outer ring (5-30 km). In column 4, the estimated coefficients are - 0.328 on the inner ring and -0.088 on the outer ring, indicating that proximate fire activity drives the bulk of the response. Evaluated at one standard deviation, an increase in recent relative to prior fire counts within 0-5 km (0.43 additional fires) is associated with a 13.2% reduction in planting TPA, or approximately 41 fewer trees per acre at the sample mean of 309 trees per acre for Douglas-fir. The same one-standard-deviation increase in the 5-30 km ring (1.68 additional fires) corresponds to a 13.8% reduction, or roughly 43 fewer trees per acre. Although the outer-ring effect remains economically meaningful, the per-fire effect is roughly three times larger in the inner ring (-28.0% vs. -8.5% per additional recent fire), consistent with landowners responding to a salient local fire signal more so than broader regional fire activity. In column 5, we estimate negative but not statistically significant effects at both the inner and outer rings, suggesting that landowners planting stands respond more so to the changes in nearby fire activity over time compared to the levels of nearby fires. In column 6, we decompose the acreage burned measure. We estimate a negative effect within 0-5 km that is marginally significant at the 10% level, and a small but statistically significant positive effect within the 5-30 km outer ring. The outer ring positive effect is the opposite sign of what we would expect, and we are cautious in interpreting it. This may reflect within-county variation in baseline planting density that our county fixed effects do not fully absorb, or it may be a chance finding given the number of fire coefficients estimated across this table.

Overall, our results in Table 3 suggest that landowners are responding to increasing nearby fire activity by lowering their planting densities, consistent with the theoretical results by Amacher et al. (2005) that landowners may respond to changes in fire arrival rates by lowering densities. The negative effect on planting density is robust to dropping the stand age and time-since-planting controls, to replacing the dependent variable with seedling trees per acre, and to restricting the sample to plantings observed within three years of the planting year, where mortality and natural-regeneration effects between planting and measurement are weakest (Appendix B.1, Table 8).

6.2 Harvest Models

In Table 4, we estimate the effects of fire activity on forest harvesting decisions. Specifically, we estimate a multinomial logit on the choice to do nothing, do a partial cut, or do a clearcut.

We observe these decision of whether to do nothing or engage in a partial or clearcut from the FIA. We also observe the timing of these decisions. In Panel A we report the estimated coefficients on the decision to partial cut vs. do nothing, and in Panel B the decision to clearcut vs. do nothing. Column 1 controls for the level of regional fire counts within 0-30 km in the 15 years prior to the management year. Column 2 controls for the total acreage burned within 0-30 km in the 15 years prior. Column 3 controls for the change in nearby wildfire counts within 0-30 km over time, the same difference measure used in our planting density model. In Columns 4, 5, and 6, each of these three measures is decomposed into 0-5 km and 5-30 km bins, a similar exercise used in our planting density model specifications. In all six columns, we also include a control that equals 1 if a FIA condition was directly burned within the previous 2 years of a given management year. In each specification, we also control for the age of the forest stand and include a set of climate controls as well as period fixed effects. Period fixed effects are used as opposed to annual fixed effects because we do not observe both partial and clear cuts in every management year in our sample. Lastly, each specification includes the condition level group means of all time-varying controls, allowing us to control for time-invariant unobserved condition level heterogeneity.

Column 1 reports estimates using fire count rather than acreage burned within the 0-30 km buffer. The average marginal effect on the probability of partial cut is 7.24×10^{-4} per additional fire. A one standard deviation increase in nearby fire count (approximately 5.1 additional fires) is associated with a 0.37 percentage point increase in the probability of choosing partial cut, or roughly a 43% increase relative to the sample mean partial-cut probability of 0.86%. In Column 2 Panel A, we estimate a positive and statistically significant effect of regional acreage burned on the decision to partial cut vs. do nothing. The average marginal effect of nearby acreage burned on the probability of partial cut is 0.42×10^{-4} per thousand acres. A one standard deviation increase in 0–30 km acreage burned (approximately 54,000 acres) is associated with a 0.23 percentage point increase in the probability that a landowner chooses partial cut over doing nothing. Relative to the sample mean partial-cut probability of 0.86%, this corresponds to roughly a 27% increase in the likelihood of selecting partial harvest in response to elevated regional fire activity. In Column 3 Panel A, we use the difference measure (change in fire counts over time) instead of the level measures. We do not estimate a statistically significant effect of this measure on the probability of partial cut.

Across both measures of fire exposure, the direction of the effect is consistent: elevated nearby fire activity raises the probability that a landowner selects partial cutting over taking no action. The fire count measure yields a somewhat larger one-standard-deviation effect than the acreage measure (43% vs. 27% relative to baseline), suggesting that landowners respond more strongly to the frequency of nearby fire events than to the total area burned. This pattern is consistent with a salience-based interpretation in which discrete fire events serve as a more visible signal of risk than cumulative burned area, which may aggregate across many small or distant fires.

In each specification in Panel A, we also control for whether the plot was directly burned within the 2 years prior to a given management year. Across all four specifications, the direct burn indicator carries a large, positive, and statistically significant coefficient on the partial-cut equation, indicating that landowners whose plots were directly burned are substantially more likely to undertake partial cutting in subsequent years than landowners on non-burned plots. However, this estimate is identified from a small number of events. Among the 444 partial cut observations in our sample, only 13 (2.9%) occur on plots that were directly burned prior to the management decision. Because we drop FIA conditions in which the partial cut was field-coded as a salvage harvest, these events represent non-salvage management responses to direct fire exposure, though we cannot fully rule out misclassification of salvage activity. The direct burn estimate should therefore be interpreted as suggestive of a meaningful post-burn behavioral response on the small set of plots experiencing direct fire, rather than as a precise population-level magnitude.

In columns 4, 5, and 6, we decompose the fire effects into 0-5 km and 5-30 km spatial rings. When the 0–30 km buffer is split into inner and outer rings, the inner-ring fire activity coefficient is statistically insignificant across all three measures. The outer-ring coefficient is positive and significant in the fire count and acreage burned specifications (columns 4 and 5), but not significant in the difference specification (column 6). The likely explanation is that the direct burn indicator and the 0–5 km fire activity measure are mechanically correlated, so the direct burn dummy absorbs much of the identifying variation in proximate fire activity. The 5–30 km measure retains its ability to identify a regional fire response. Taken together, the columns 4 through 6 results suggest that landowners respond both to direct fire exposure on their own land and to broader regional fire activity in the surrounding landscape, with the inner-ring signal in the no-direct-burn subpopulation being too weak to detect separately from the direct burn effect. Overall, our results suggest that landowners exposed to nearby increases in fire activity are more likely to engage in partial cut harvests.

In Panel B, we estimate the effect of fire activity on the likelihood of clearcut harvesting vs. doing nothing. In columns 1 and 2, we estimate negative effects of fire activity on the likelihood of clearcut harvesting, while in column 3 the change-in-fire-counts measure carries a small positive sign. None of these aggregated fire coefficients are statistically distinguishable from zero at conventional levels. We estimate positive and statistically significant effects of being directly burned on the likelihood of doing a subsequent clearcut harvest. However, these results are estimated off only 2 conditions in our sample that were directly burned and subsequently clearcut, as we exclude any plots that were marked as salvaged clearcut. Taken with Panel A, we believe that we have suggestive evidence that being directly burned increases the likelihood of doing both a partial cut or a clearcut vs. doing nothing.

In columns 4, 5, and 6, we again decompose the effect of fire into a nearby and distant spatial buffer. In column 5, we estimate a positive and statistically significant effect of nearby fire activity on the likelihood of clearcut harvesting, however, the coefficient on the direct burn dummy is now not statistically significant, likely driven by a similar story as panel A. These two variables are mechanically correlated, leaving little variation for each one to be separately identified. However, in column 5, we estimate a negative and statistically significant effect of distant fire activity on the likelihood of clearcut harvesting vs. doing nothing. In column 4, the fire-count coefficients on the clearcut equation are statistically insignificant on both rings: the inner-ring coefficient is positive and the outer-ring coefficient is negative. In column 6, which uses the change-in-fire-counts measure, we also do not estimate any statistically significant fire-activity effects on the clearcut equation.

Taken together, the Panel A and Panel B results suggest that elevated regional fire activity shifts landowners away from clearcutting and toward partial cutting. To formally test whether the response to fire differs across harvest types, we test the null hypothesis that the fire activity coefficients are equal across the partial cut and clearcut equations. Rejection of this null is direct evidence of substitution between harvest types, testing whether landowners are not simply more or less likely to harvest in response to fire, but are reallocating across harvest intensities.

The substitution test results are reported in the bottom panel of Table 4. For the aggregated 0–30 km acreage measure in column 2, we reject equality at the 5% level ($\chi^2 = 4.57$, $p = 0.032$). The fire count measure in column 1 yields a similar result, though weaker ($\chi^2 = 2.85$, $p = 0.091$). The change-in-fire-counts measure in column 3 does not reject the null ($\chi^2 = 0.95$, $p = 0.329$). In the decomposed specifications, the substitution test is sharper. In column 5 we reject equality at both the inner ring ($\chi^2 = 7.80$, $p = 0.005$) and the outer ring ($\chi^2 = 10.84$, $p = 0.001$). Column 4 produces consistent though weaker results, with rejection at the outer ring ($\chi^2 = 5.05$, $p = 0.025$), and we are unable to reject the null at the 10% level in the inner-ring ($\chi^2 = 2.67$, $p = 0.102$). Column 6, the decomposed difference measure, rejects only at the inner ring ($\chi^2 = 4.56$, $p = 0.033$). Across the fire-count and acreage measures and across both spatial scales, the data reject the hypothesis that landowners respond to fire activity identically across harvest types. Among plot-years in which any harvest is undertaken, partial cuts represent 41% of decisions (444/1,084) and clearcuts 59%; our estimates in Table 4 imply that elevated regional fire activity shifts this composition away from clearcutting and toward partial cutting. The full coefficient set for the headline MNL specifications is reported in Appendix C.1, Table 9. As a robustness check on the decomposed-ring specifications, we re-estimate the model dropping either the 0–5 km inner ring or the direct-burn dummy (the two are mechanically correlated); the 5–30 km outer-ring coefficients are largely unchanged either way (Appendix C.2, Table 11). We also re-estimate the model as a nested logit with partial cut and clearcut grouped in a "cut" nest above the no-action alternative; the qualitative result is preserved, although the dissimilarity parameter on the cut nest is significantly less than one, indicating that the IIA assumption does not strictly hold (Appendix C.3, Table 12).

Table 4 shows landowners shift toward partial cuts on the extensive margin in response to fire exposure. Appendix Table 13 shows that conditional on a partial cut occurring, higher local fire exposure also shifts the timing earlier in the rotation, as predicted by Patto and Rosa (2022). Both results point to the same underlying behavioral mechanism: landowners reduce stand exposure to fire by partial-harvesting, and they do so at younger stand ages when fire risk is elevated.

To translate these estimates into landscape-scale implications, we next turn to a Monte Carlo simulation that maps the MNL marginal effects onto counterfactual fire regimes. The simulation allows us to quantify how much of the observed shift in management composition is attributable to recent fire activity, and to ask what the management mix would have looked like under historical fire conditions.

6.3 Monte Carlo Simulation

We translate the estimated harvest-choice and planting-density models into the consequences of a shift in the fire regime through a Monte Carlo simulation. The exercise asks what the two management margins look like not at the margin of a single additional fire, but when the entire fire environment moves from its historical level to the levels observed in recent years. We take the conditions in the harvest-choice estimation sample and, under a given fire regime, draw each stand's annual management action from the multinomial logit of Table 4. A stand that is not cut in a given year remains in the simulation and faces the choice again the following year. Once a stand is partially cut or clearcut, it leaves the simulation and is not projected forward. For the stands that realize a clearcut, we then predict planting density from the model in Table 3 column 1. We run the simulation under three fire regimes, constructed from each stand's average observed fire exposure during the pre-2010 (low), post-2010 (elevated), and 2020 (extreme) periods, and we repeat it over 1,000 iterations with common random numbers so that differences across regimes reflect the change in fire input rather than simulation noise.

Table 5 reports the harvest-composition response. As the fire regime intensifies, the share of harvests that are clearcuts falls and the share that are partial cuts rises. Across all stands, the partial-cut share rises from 11.4 percent under the low regime to 13.5 percent under the elevated regime and 16.5 percent under the extreme regime, an increase of 2.2 and 5.2 percentage points respectively. The shift concentrates in the high-fire regions of our sample: under the extreme fire regime the partial-cut share rises by 7.4 percentage points east of the Cascades and by 13.8 points across the rest of California, compared with just 1.0 point west of the Cascades and 3.0 points on the NW California coast (Table 5; Appendix Figure 8 maps the four regions).

Table 6 reports the planting-density response at the stands that realize a clearcut. Mean predicted planting density falls from 264 trees per acre under the low regime to 252 under the extreme regime, a reduction of 12 trees per acre, or 4.5 percent; across the four regions the reduction ranges from 4.2 percent west of the Cascades to 7.2 percent on the NW California coast (Table 6). The number of clearcuts per iteration falls across fire regimes, from 4,677 under the low regime to 4,405 under the extreme regime, reflecting the same composition shift documented in Table 5.

Taken together, the two margins move in the same direction. As fire activity rises, landowners substitute partial cuts for clearcuts, and the stands that are still clearcut are replanted at lower densities. Both responses are consistent with management that reduces a stand's exposure to fire.

7 Discussion

Wildfire intensity and severity are increasing in the Western United States, and this trend is expected to continue under climate change (Westerling et al., 2006; Abatzoglou and Williams, 2016). Forest management practices can influence future risk, yet we know very little about how management has responded to elevated risk. In this paper, we provided evidence that forest managers respond to increased fire activity on multiple margins. First, on the intensive margin, managers respond to fire by reducing their planting densities, consistent with theoretical predictions from Amacher et al. (2005). Second, managers respond to increasing wildfire activity by engaging in more partial cut harvests, often referred to as commercial cutting. We also provide suggestive evidence that this increase in partial cut harvests is coming at the expense of less clearcut harvesting, a finding in line with predictions from Patto and Rosa (2022).

Taken together, these findings highlight adaptive behavior to increasing risk. Each of these behaviors is predicted to reduce a landowner's own exposure to fire. Lowered planting densities lead to less fuels, a common recommendation to lower fire risk (Agee and Skinner, 2005; Reynolds et al., 2013). Additionally, Zald and Dunn (2018) show that intensively managed forest plantations burn more severely than neighboring, less actively managed public lands, with the proposed mechanism being federal lands have more heterogeneous, fire resilient structures. Our work finds that landowners may be substituting clearcut, plantation like forest harvest decisions with more partial cut harvesting, which may lead to more heterogeneous canopies and lower fuels, ultimately reducing landowner fire risk. Our findings provide the first large-scale, empirical evidence that landowners are adapting to a changing risk environment through actions predicted in natural resource economic theory (Amacher et al., 2005; Patto and Rosa, 2022).

To mitigate increasing risk, public policy has sought to incentivize fuels treatments on private lands, through things such as cost sharing programs. In the case of fuels treatment work like pre-commercial thinnings, we provide evidence that these programs may be needed. We find no evidence that landowners engage in more precommercial thinnings, an activity that does not generate any immediate revenue but incurs fixed costs. This is suggestive that cost sharing programs targeted specifically at these types of costly activities may be beneficial, as landowners don't fully internalize the benefits of such actions. However, we find that landowners do engage in more partial cut harvests, an activity that is a rational response to perceived increases in risk, but one that also generates revenue for the landowner. Cost sharing programs may be better directed away from these types of activities.

Our work comes with several limitations. First, we do not measure how these observed adaptation behaviors will influence future fire risk, which in turn will influence future forest management decisions. Future work may seek to provide empirical evidence on how private forest management activities influence fire spread and severity. Additionally, our analysis does not observe prescribed burning activities. Although prescribed burning on private forestlands in the West is relatively uncommon due to risk of spread and existing liability laws (Miller et al., 2020), future work should examine how prescribed burning activities respond to changes in wildfire risk on western private lands. Hashida et al. (2025) examine this question for the southeastern United States, but a similar empirical exercise for the western United States, where prescribed burning is far less common on private land, remains an open question. Additionally, we do not observe neighboring landowner fuel management activities. It may be the case that nearby fuels management work on neighboring private and public lands crowds out or incentivizes additional investments on people's own land. We believe this is a fruitful area for future research. Additionally, privately optimal landowner adaptation may affect ecosystem service provision, such as carbon sequestration and wildlife habitat. Quantifying the effects of private adaptation on these public goods is an area for future research. Additionally, our estimates capture an average response across landowner types, but adaptation behavior likely varies substantially across ownership categories. Industrial timberland owners, family forest owners, and state agencies operate under different objective functions, planning horizons, and information environments, and may respond to elevated fire risk in different ways. We do not directly observe these subgroup ownership classifications in our data. Future work estimating heterogeneous responses by ownership type would help identify which landowner segments are adapting most actively, and where targeted policy may have the largest effect. Finally, our sample is restricted to private and state timberland in Oregon, California, and Washington. While these states contain a substantial share of fire-exposed private forestland in the western United States, adaptation responses may differ in the interior West, the Rocky Mountains, or the Southeast, where forest composition, ownership structure, market access, and fire regimes all differ from the western United States. Extending this analysis to other fire-prone regions and forest types would clarify the external validity of our findings and help build a more complete picture of how private forest management is adapting to a changing fire regime.

Overall, our results provide evidence of climate change adaptation happening within the forestry industry. This behavior is expected to influence future risk and severity, and is consistent with natural resource economic theory. Forest landowners are asset managers, and are shifting their management strategies to reduce exposure to climate risk.

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Figures and Tables

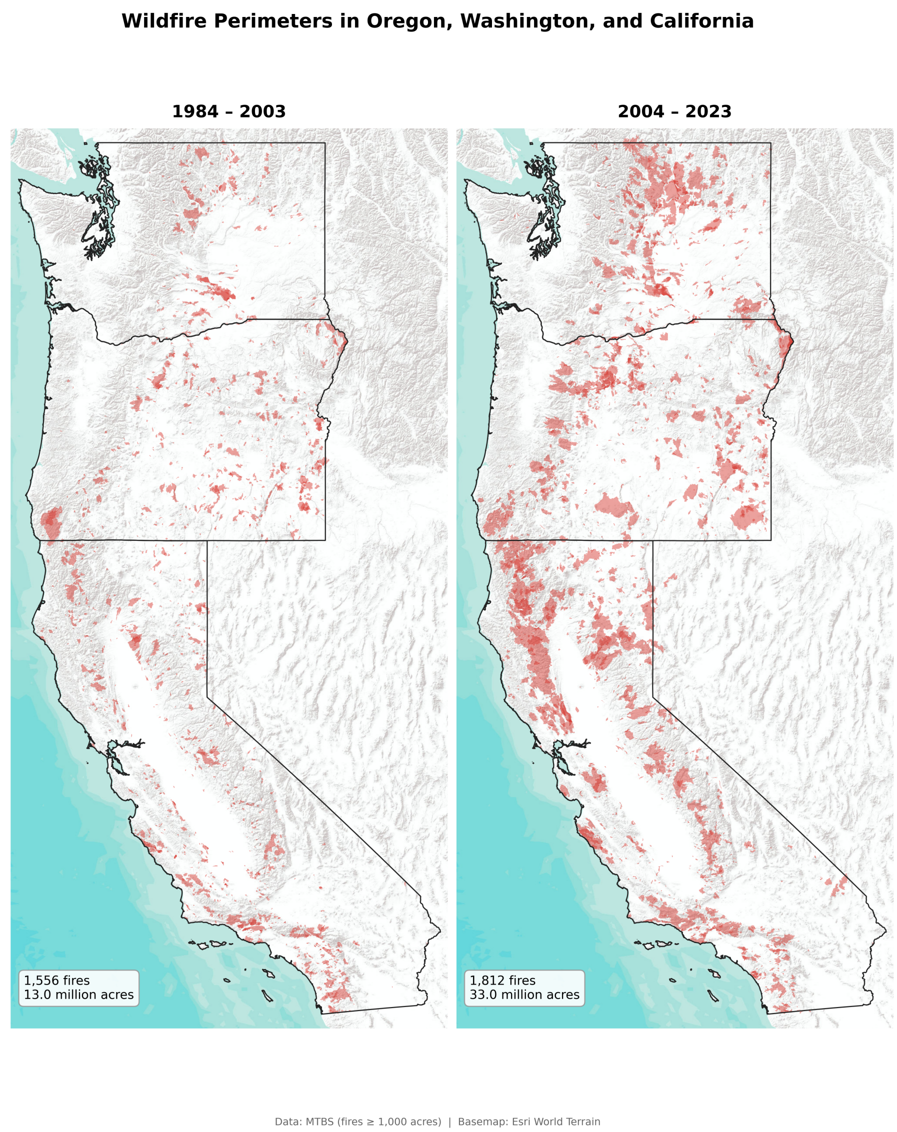

Figure 1: Burned area in the western United States, 1984–2003 vs. 2004–2023

Notes: Fire perimeters from the Monitoring Trends in Burn Severity (MTBS) database, restricted to fires of at least 1,000 acres in California, Oregon, and Washington. The left panel shows the 1,556 fires that burned 13.0 million acres during 1984–2003; the right panel shows the 1,812 fires that burned 33.0 million acres during 2004–2023. The total area burned in the western United States more than doubled between the two periods. Basemap: Esri World Terrain.

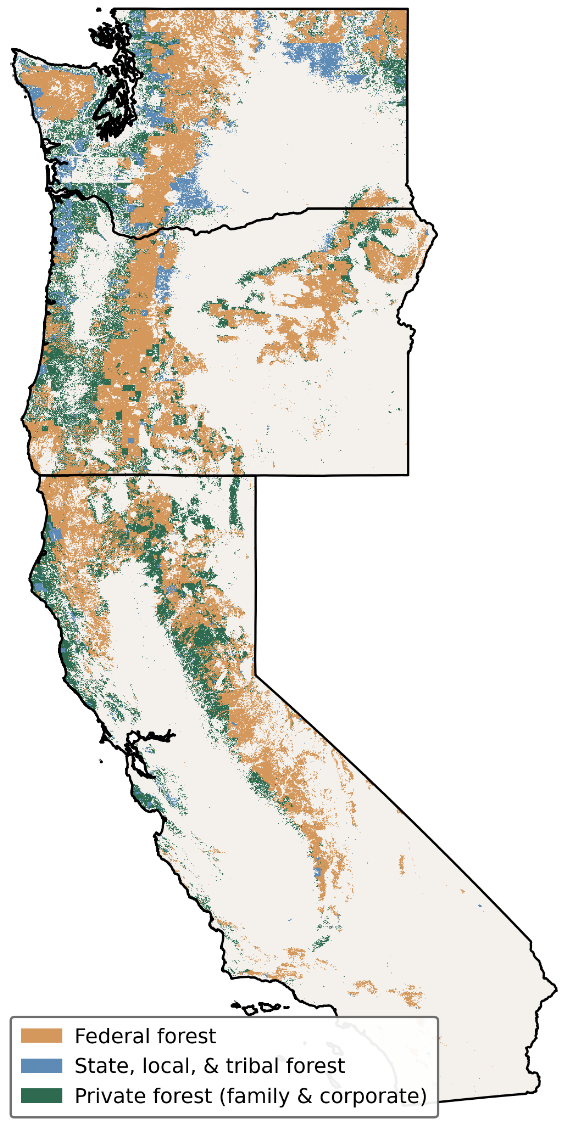

Figure 2: Forest land ownership in California, Oregon, and Washington

Notes: Forest land in California, Oregon, and Washington classified by ownership type. Federal forest is concentrated in the Cascades, Sierra Nevada, Klamath, Blue Mountains, and Olympic ranges; private forest is most extensive in the Oregon Coast Range, western Washington, and northern California; state, local, and tribal forest is most visible in Washington (Department of Natural Resources lands) and parts of northern California. The western forest landscape is a mosaic of federal and non-federal ownership, in contrast to the predominantly private forest land of the southeastern United States. Our estimating sample (Figure 3) is restricted to private and state timberland. Ownership data from Harris et al. (2025); state boundaries shown in black.

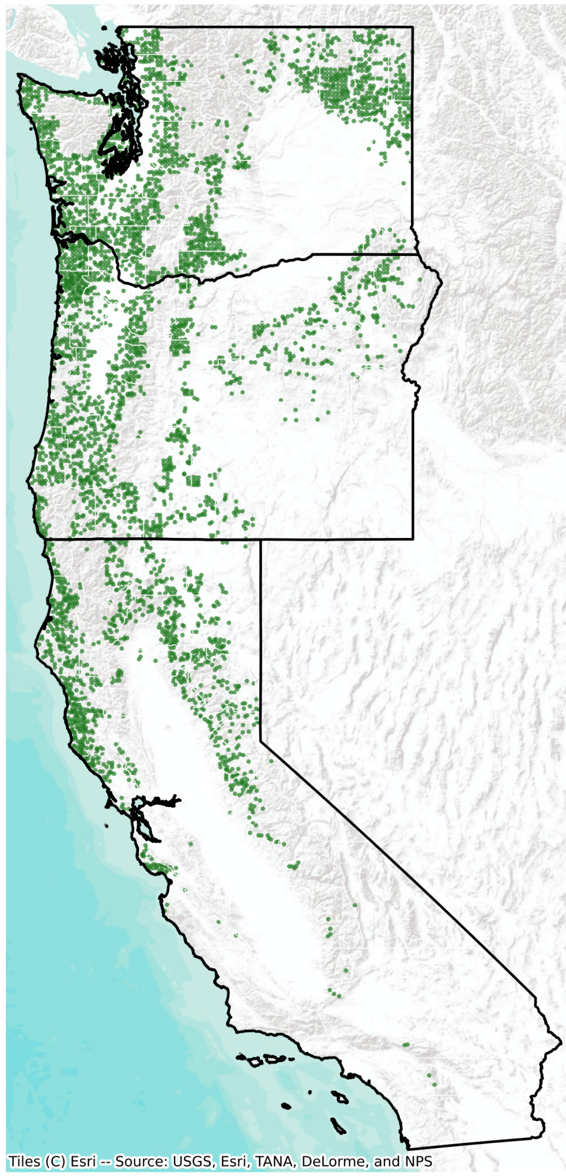

Figure 3: Non-federal FIA plots in the harvest-choice estimating sample

Notes: Each green point represents one of the 4,367 unique FIA plots (5,277 condition–year units) included in the harvest-choice estimating sample for California, Oregon, and Washington. The sample restricts to private and state timberland with stand age at least 30 years, dropping any unit that ever recorded a salvage clearcut or salvage partial cut. State boundaries shown in black. Basemap: Esri World Terrain.

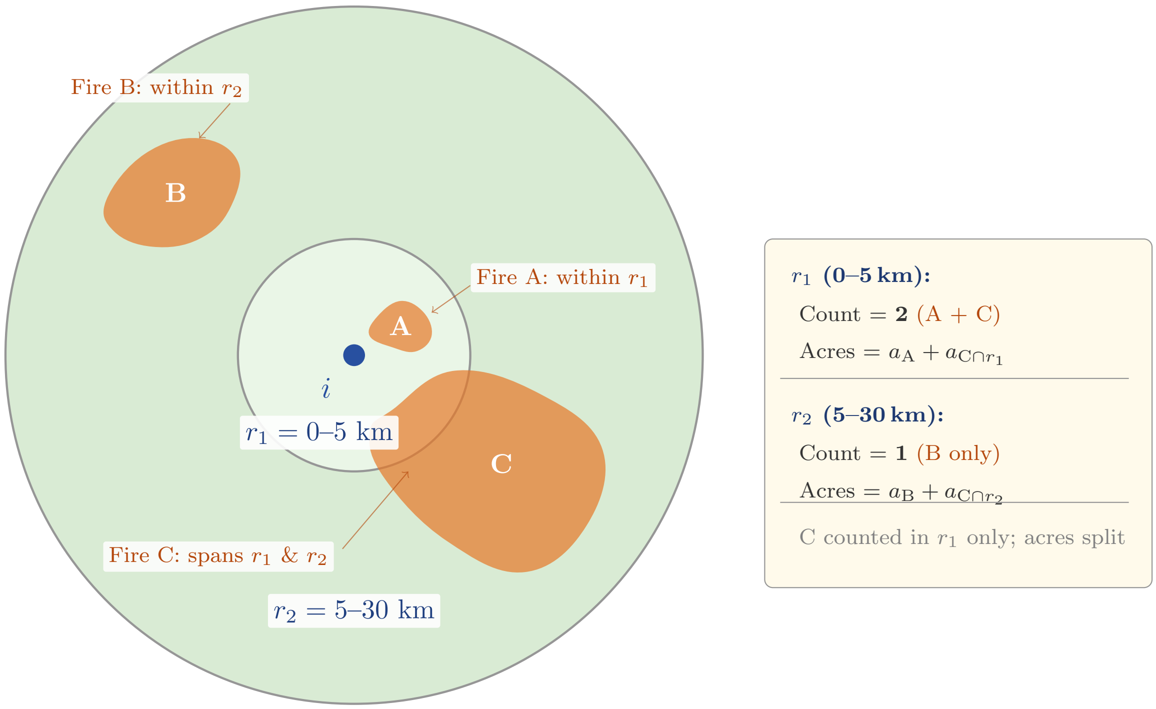

Figure 4: Construction of plot-level fire exposure variables

Notes: The figure illustrates how we measure fire exposure for a management decision observed on FIA plot i. Around each plot we define two concentric zones: an inner ring r_1 spanning 0–5 km and an outer ring r_2 spanning 5–30 km. Within each zone, over a look-back window ending in the year of the management decision, we sum the number of distinct fires and the total acreage burned. Fire A lies entirely within r_1 and Fire B entirely within r_2, so each contributes to a single zone. Fire C spans both zones: it is counted once in the inner ring, while its burned acreage is apportioned across zones according to the share of its perimeter falling within each. The plot-level fire measures are thus the fire count and burned acreage in each ring, together with the change in each across successive look-back windows—the Δ variables, whose construction is shown in Figure 5. Fire perimeters are drawn from the Monitoring Trends in Burn Severity (MTBS) database and include all fires of at least 1,000 acres. We construct each measure over 5, 10, and 15-year look-back windows.

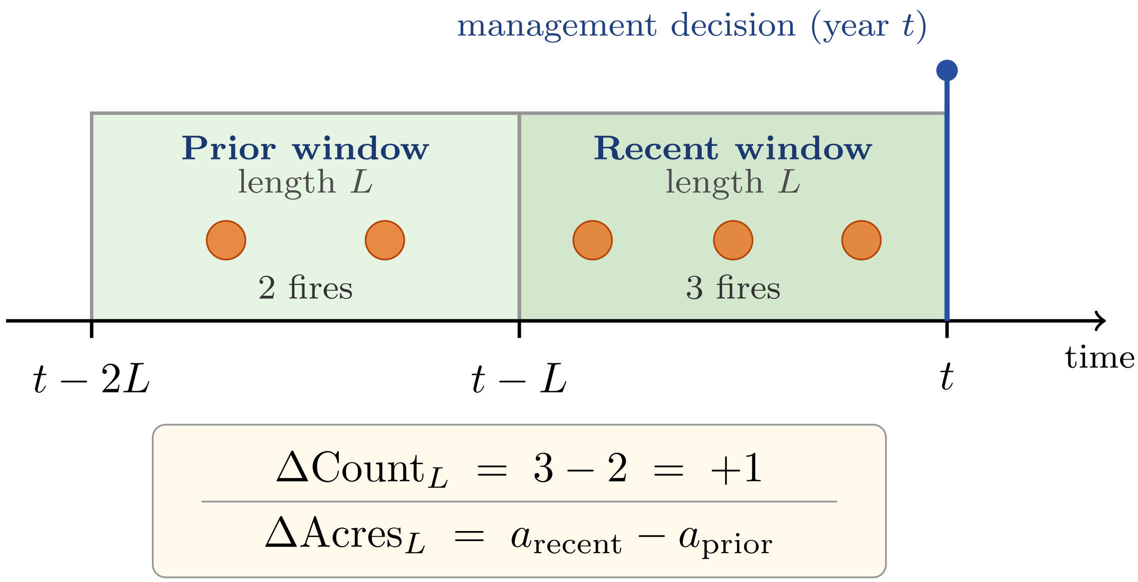

Figure 5: Construction of the change-in-fire-activity (Δ) variables

Notes: The figure illustrates how we measure changes in local fire activity over time, which define our Δ variables. For a management decision observed in year t and a look-back length L, we compare fire activity in the recent window $[t-L, t)$ against the immediately preceding window $[t-2L, t-L)$. Each orange marker denotes one fire ($\geq$ 1,000 acres). In the example, three fires fall in the recent window and two in the prior window, so the change in fire count is $\Delta\text{Count}_L = 3-2 = +1$, indicating intensifying local fire activity; the change in burned acreage, $\Delta\text{Acres}_L = a_{\text{recent}} - a_{\text{prior}}$, is defined analogously, where a_{recent} and a_{prior} denote total acres burned in the recent and prior windows. We construct these Δ measures separately within each spatial ring (r_1 and r_2 in Figure 4), for both fire counts and acreage burned, and over 5, 10, and 15-year window lengths. Positive values indicate that recent fire activity exceeds that of the preceding period.

Table 1: Summary Statistics: Planting Density Sample

Unit of observation: recently planted FIA plot-conditions		
Sample size		
Conditions (observations)	556	
Plots	530	
Counties (clusters)	67	
States (OR / WA / CA)	280 / 214 / 62	
Measurement years	2004–2024	
Planting years	2004–2023	
	Mean	Std. Dev.
Outcome: planting TPA, dominant species		
All conditions	355.5	566.5
Douglas-fir (n=315)	309.0	233.9
Other (n=241)	416.3	814.8
Time since planting (yrs)	3.9	2.5
Wildfire exposure (lagged, pre-planting)		
Fire count, 0–30 km, 10-yr	1.24	2.66
Δ Fire count, 0–30 km, 10-yr	0.50	1.79
Fire count, 0–5 km, 10-yr	0.13	0.43
Fire count, 5–30 km, 10-yr	1.12	2.40
Post-burn planting (share)	7.2%	—
Controls		
Stand age at meas. (yrs)	7.2	18.1
Elevation (km)	1.81	1.41
Slope (%)	32.0	23.2
15-yr GS max VPD (hPa)	13.65	3.75
15-yr GS precip (mm)	329.8	126.9
15-yr GS mean temp (°C)	13.00	1.33

Notes: Unweighted summary statistics over the estimating sample of the planting density regression (column 1 of Table 3): weighted least squares of log planting TPA on the 0–30 km 10-year change in wildfire count, for newly established plantations in OR, WA, and CA. Wildfire variables are lagged to be strictly pre-planting and span the 10 years before planting. Post-burn planting equals one when the condition itself burned before planting.

Table 2: Summary Statistics: Harvest Choice Sample

Unit of observation: annual condition-year observations		
Sample size		
Condition-years (observations)	51,451	
Unique conditions	5,277	
Plots (clusters)	4,367	
States (WA / OR / CA)	19,731 / 18,360 / 13,360	
Years covered	2001–2024	
	Mean	Std. Dev.
Outcome shares		
No action	97.89%	—
Partial cut	0.86%	—
Clearcut	1.24%	—
Wildfire exposure (lagged, 15-yr)		
Acreage burned, 0–30 km (1,000 ac)	29.86	54.44
Fire count, 0–30 km	3.97	5.10
Direct burn, prior 2 yrs (share)	0.54%	—
Controls		
Stand age (yrs)	74.7	39.2
Elevation (km)	2.44	1.70
Slope (%)	29.6	24.0
15-yr GS max VPD (hPa)	15.90	4.65
15-yr GS precip (mm)	243.4	131.3
15-yr GS mean temp (°C)	13.17	2.00

Notes: Unweighted summary statistics over the estimating sample of the multinomial logit of annual management action (Table 4, column 1) on private and state timberland in OR, CA, and WA, 2001–2024, restricted to stand age ≥ 30 with salvage harvests excluded. Wildfire exposure is the cumulative sum over the 15 years prior to the management year within 0–30 km; acreage in thousands of acres. Direct burn equals one when the condition itself burned in either of the two prior years.

Table 3: Planting Density and Wildfire Exposure

	Aggregated (0–30 km)			Decomposed (0–5 & 5–30 km)		
	(1) Δ Fire count (10-yr)	(2) Fire count (15-yr)	(3) Acreage burned (15-yr)	(4) Δ Fire count (10-yr)	(5) Fire count (15-yr)	(6) Acreage burned (15-yr)
Wildfire exposure, 0–30 km	-0.0987***	-0.0096	0.0028			
	(0.0237)	(0.0373)	(0.0019)			
0–5 km				-0.3284***	-0.1791	-0.0431*
				(0.1228)	(0.1920)	(0.0230)
5–30 km				-0.0884***	-0.0029	0.0044**
				(0.0239)	(0.0350)	(0.0022)
Post-burn planting	0.0584	-0.1142	-0.2764	0.2207	0.0412	0.0718
	(0.2614)	(0.2511)	(0.2584)	(0.2721)	(0.2996)	(0.3149)
Time since planting (yrs)	0.0580**	0.0556***	0.0545**	0.0585**	0.0554**	0.0555**
	(0.0234)	(0.0216)	(0.0215)	(0.0232)	(0.0217)	(0.0217)
Stand age at meas. (yrs)	0.0015	0.0028	0.0026	0.0014	0.0028	0.0021
	(0.0038)	(0.0025)	(0.0025)	(0.0038)	(0.0025)	(0.0027)
Site class dummies	Yes	Yes	Yes	Yes	Yes	Yes
Topographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Planting year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	556	613	613	556	613	613
Counties (clusters)	67	68	68	67	68	68
R^2	0.365	0.314	0.316	0.369	0.315	0.321

Notes: Weighted least squares estimates of log Planting TPA (dominant species) on cumulative wildfire-exposure variables for newly established plantations in OR, CA, and WA. Each column uses a single fire-exposure regressor. The Δ fire-count specifications (columns 1, 4) take the count of fires in the 10 years before planting minus the count in the prior decade. The fire-count specifications (columns 2, 5) count fire events within the indicated radius over the 15 years before planting. The acreage-burned specifications (columns 3, 6) sum acres burned within that radius and 15-year window, in thousands of acres. The Δ fire-count specifications use a 10-year window because the 15-year Δ would require 30 years of pre-planting fire history and would lose observations. Aggregated specifications (columns 1–3) enter exposure within 0–30 km as a single regressor; decomposed specifications (columns 4–6) split it into 0–5 km and 5–30 km rings entered jointly. Post-burn planting is a dummy equal to 1 when the condition itself burned at some point before the planting event. Topographic controls are elevation (km), slope, and aspect; climate controls are 15-year growing-season averages of max VPD and max temperature; site class is the FIA seven-level site productivity classification. Weighted by condition proportion; standard errors clustered by state-county. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Multinomial Logit of Forest Management Action

	Aggregated (0–30 km)			Decomposed (0–5 & 5–30 km)		
	(1) Fire count (15-yr)	(2) Acreage burned (15-yr)	(3) Δ Fire count (10-yr)	(4) Fire count (15-yr)	(5) Acreage burned (15-yr)	(6) Δ Fire count (10-yr)
Panel A: Partial Cut vs. Do Nothing						
Wildfire exposure, 0–30 km	0.0762***	0.0044**	-0.0109			
	(0.0282)	(0.0019)	(0.0205)			
0–5 km				-0.1851	-0.0218	-0.1431
				(0.1632)	(0.0403)	(0.1049)
5–30 km				0.0936***	0.0051**	-0.0032
				(0.0307)	(0.0023)	(0.0217)
Direct burn	1.4753***	1.2369***	1.5678***	1.6156***	1.3683***	1.6423***
	(0.3927)	(0.4102)	(0.3963)	(0.4072)	(0.4224)	(0.4063)
Panel B: Clearcut vs. Do Nothing						
Wildfire exposure, 0–30 km	-0.0151	-0.0035	0.0174			
	(0.0466)	(0.0032)	(0.0209)			
0–5 km				0.3151	0.1777***	0.2034
				(0.2594)	(0.0602)	(0.1261)
5–30 km				-0.0361	-0.0084**	0.0068
				(0.0492)	(0.0034)	(0.0219)
Direct burn	2.5211***	3.1035***	2.4088***	2.2910***	1.5735	2.2377***
	(0.9045)	(1.1873)	(0.8572)	(0.8839)	(1.1248)	(0.8452)
Average Marginal Effects on outcome probabilities ($\times 10^{-4}$, SE in parens.)						
on Pr(Partial Cut):						
0–30 km	7.24*** (2.69)	0.42** (0.18)	-1.07 (1.97)			
0–5 km				-17.83 (15.47)	-2.23 (3.81)	-13.95 (10.10)
5–30 km				8.90*** (2.94)	0.49** (0.22)	-0.32 (2.09)
on Pr(Clearcut):						
0–30 km	-1.95 (5.80)	-0.44 (0.40)	2.24 (2.68)			
0–5 km				39.42 (32.35)	22.12*** (7.51)	26.22 (16.20)
5–30 km				-4.59 (6.14)	-1.05** (0.43)	0.88 (2.81)
Substitution test (H_0: equal fire coef. across equations)						
0–30 km, χ^2	2.85	4.57	0.95			
p	0.091	0.032	0.329			
0–5 km, χ^2				2.67	7.80	4.56
p				0.102	0.005	0.033
5–30 km, χ^2				5.05	10.84	0.11
p				0.025	0.001	0.743
Observations	51,451	51,451	49,477	51,451	51,451	49,477
Plots (clusters)	4,367	4,367	4,362	4,367	4,367	4,362
Log pseudolikelihood	-4404.5	-4402.3	-4330.0	-4402.3	-4395.0	-4328.4
Pseudo R^2	0.128	0.128	0.122	0.128	0.130	0.123

Notes: Multinomial logit of annual forest management action on condition–year observations for private and state timberland in OR, CA, and WA, 2001–2024; do-nothing is the base outcome. Sample restricted to stand age $\geq$ 30 with salvage harvests excluded. The fire-count specifications (columns 1, 4) count fires within the indicated radius over the 15 years prior; the acreage-burned specifications (columns 2, 5) sum acres burned within that radius and 15-year window, in thousands of acres; the Δ fire-count specifications (columns 3, 6) take the count of fires in the 10 years before the management year minus the count in the prior decade. The Δ specifications use a 10-year window because the 15-year Δ would require 30 years of pre-decision fire history and would lose observations. Aggregated specifications enter exposure within 0–30 km as a single regressor; decomposed specifications split it into 0–5 km and 5–30 km rings entered jointly. Direct burn is a dummy equal to 1 when the condition itself burned in either of the two prior years. AMEs are evaluated at the sample mean of every covariate and scaled by 10^4. All specifications include stand age, climate controls, CRE group means, and period FE. Weighted by the t-1 condition proportion; standard errors clustered by plot. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Simulated Effect of Wildfire Regimes on Harvest Composition

	Fire regime			Change vs. low (Δ)	
	Low (Pre-2010)	Elevated (Post-2010)	Extreme (2020)	Elevated − Low	Extreme − Low
All plots ($N = 5,277$)					
Clearcut	88.64	86.49	83.48	−2.15	−5.16
Partial cut	11.36	13.51	16.52	+2.15	+5.16
				[1.59, 2.77]	[4.47, 5.89]
West of Cascades ($N = 2,424$)					
Clearcut	93.41	93.01	92.39	−0.40	−1.02
Partial cut	6.59	6.99	7.61	+0.40	+1.02
				[-0.08, 0.87]	[0.45, 1.57]
East of Cascades ($N = 1,537$)					
Clearcut	81.76	78.12	74.37	−3.64	−7.39
Partial cut	18.24	21.88	25.63	+3.64	+7.39
				[2.34, 5.07]	[5.86, 8.98]
NW California coast ($N = 440$)					
Clearcut	91.51	90.18	88.49	−1.33	−3.02
Partial cut	8.49	9.82	11.51	+1.33	+3.02
				[-0.68, 3.18]	[0.68, 5.45]
Rest of California ($N = 876$)					
Clearcut	86.05	81.26	72.28	−4.79	−13.77
Partial cut	13.95	18.74	27.72	+4.79	+13.77
				[2.74, 6.74]	[11.30, 16.44]
Iterations		1,000			
Projection horizon		through 2100			

Notes: Monte Carlo simulation of private and state timberland stands in OR, CA, and WA, projected annually from each stand's entry (stand age ≥ 30) through 2100 over 1,000 iterations with common random numbers. The first panel uses all 5,277 stands; the remaining panels partition them into four regions—OR/WA west of the Cascade crest, OR/WA east of the crest, the NW California coast (Del Norte, Humboldt, Mendocino), and the rest of California. Each year a stand's harvest choice—none, partial cut, or clearcut—is drawn from the multinomial logit of Table 4, with the first harvest absorbing. The three regimes fix every stand's fire exposure at its observed average level over the pre-2010 (low), post-2010 (elevated), and 2020 (extreme) periods; the harvest model uses 30 km, 15-year acreage burned, whose regime means are 18.8, 51.5, and 82.6 thousand acres. Δ columns report the change in the percentage-point share of each harvest type relative to the low regime. Bracketed 95% intervals are the 2.5th–97.5th percentiles of the 1,000 per-iteration, common-random-number–paired differences, and reflect Monte Carlo (simulation) uncertainty holding the estimated coefficients fixed. All stands are harvested within the horizon, so harvest shares also describe the composition of cuts. Replanting density results from the same simulation appear in Table 6.

Table 6: Simulated Effect of Wildfire Regimes on Planting Density at Realized Clearcut Events

	Low (Pre-2010)	Elevated (Post-2010)	Extreme (2020)	Δ Elevated − Low	Δ Extreme − Low
Fire input applied to the planting density model					
Sample-mean 10-yr Δ fire count	0.67	0.78	1.07	+0.10	+0.40
All realized clearcut events					
Mean predicted TPA	264.3 [261.0, 267.4]	260.7 [257.6, 264.0]	252.4 [249.2, 255.7]	-3.6 (-1.35%) [-5.8, -1.3]	-12.0 (-4.53%) [-14.8, -9.0]
Clearcut events per iteration	4677.4 [4633, 4719]	4563.9 [4511, 4608]	4405.1 [4352, 4450]	-113.5 [-146, -84]	-272.4 [-311, -236]
West of Cascades					
Mean predicted TPA	276.3 [273.5, 279.2]	273.1 [270.1, 275.9]	264.7 [261.9, 267.5]	-3.2 (-1.17%) [-4.0, -2.6]	-11.6 (-4.21%) [-12.6, -10.6]
Clearcut events per iteration	2264.3 [2240, 2288]	2254.6 [2229, 2278]	2239.4 [2213, 2265]	-9.7 [-21, +2]	-24.8 [-38, -11]
East of Cascades					
Mean predicted TPA	180.8 [174.1, 187.1]	177.4 [170.1, 184.4]	170.5 [162.9, 177.8]	-3.4 (-1.87%) [-9.4, +1.8]	-10.3 (-5.70%) [-17.2, -3.9]
Clearcut events per iteration	1256.7 [1228, 1285]	1200.8 [1170, 1230]	1143.1 [1111, 1175]	-55.9 [-78, -36]	-113.6 [-138, -90]
NW California coast					
Mean predicted TPA	483.7 [462.5, 502.9]	471.2 [450.6, 491.2]	449.1 [427.5, 469.1]	-12.4 (-2.57%) [-26.4, +0.9]	-34.6 (-7.15%) [-50.1, -19.9]
Clearcut events per iteration	402.6 [391, 414]	396.8 [384, 409]	389.3 [377, 402]	-5.9 [-14, +3]	-13.3 [-24, -3]
Rest of California					
Mean predicted TPA	250.4 [243.2, 258.2]	245.0 [236.0, 253.0]	235.6 [225.3, 244.7]	-5.4 (-2.16%) [-12.1, +0.3]	-14.8 (-5.90%) [-23.7, -6.7]
Clearcut events per iteration	753.8 [734, 773]	711.8 [689, 733]	633.2 [609, 657]	-42.0 [-59, -24]	-120.6 [-144, -99]

Notes: Per-iteration aggregates of realized clearcut events from the 1,000-iteration Monte Carlo simulation with common random numbers across the three fire regimes. The MNL harvest-choice draws use each plot's own regime-specific fire-Δ value; the planting density model is then applied only at conditions that realize a clearcut, with the fire input set to the regime sample-mean of the 10-year Δ fire-count variable across all 5,277 conditions in the simulation universe (0.67 / 0.78 / 1.07). Stand age and time since planting are held at their sample means (7.2 and 3.9 years, respectively); the remaining density-model covariates take each plot's own values. Duan smearing factor applied. Below the full sample, four regions partition it: OR/WA west of the Cascade crest, OR/WA east of the crest, the NW California coast (Del Norte, Humboldt, Mendocino), and the rest of California. Point estimates are means across iterations; brackets are 2.5–97.5 percentile cross-iteration intervals. Δ columns are per-iteration paired differences aggregated to point and 95% interval.

A Data and Sample Construction

A.1 Fire Variable Construction

Our wildfire data come from the Monitoring Trends in Burn Severity (MTBS) database (Eidenshink et al., 2007), which records the perimeter, ignition date, and burned area of every U.S. wildfire of at least 1,000 acres. We link MTBS fires to each FIA plot using the plot's confidential unfuzzed coordinates and construct plot-level measures of nearby fire exposure that vary across three dimensions: spatial ring radius, temporal look-back window, and fire-activity measure.

Spatial rings. For each FIA plot, we draw concentric circles of radius 5, 10, 15, 20, 25, and 30 km around the plot and count or sum properties of all MTBS fire perimeters that intersect each circle. Figure 4 illustrates the geometry, including how fires that span ring boundaries are apportioned. For the main results in the body of the paper we work with the aggregated 0–30 km ring and with the decomposed 0–5 km / 5–30 km annulus, but all six rings are constructed for every plot–year so that we can examine the sensitivity of results to alternative spatial scales.

Look-back windows. For a management decision observed in year t on plot i, each fire variable is computed over a fixed pre-decision window. We build three look-back windows: 5 years $[t-5, t-1]$, 10 years $[t-10, t-1]$, and 15 years $[t-15, t-1]$. The longer windows capture cumulative regional fire activity, while the shorter windows are more sensitive to recent salience. By construction every fire variable enters the model strictly before the management decision it is meant to predict.

Fire-activity measures. Within each ring–window combination we construct four measures of nearby fire activity:

1. **Fire count**: the number of distinct fires whose perimeter intersects the ring during

the look-back window.

2. **Acreage burned**: the sum of fire acreage within the ring during the look-back window. For fires that span the ring boundary, acreage is apportioned according to the share of the fire perimeter falling within the ring.

3. **Change in fire count**: the count in the recent window $[t-w,\, t-1]$ minus the count in the immediately preceding window of equal length $[t-2w,\, t-w-1]$. Positive values indicate intensifying local fire activity.

4. **Change in acreage burned**: the acreage in the recent window minus the acreage in the immediately preceding window, defined analogously to the count change.

Figure 5 illustrates the construction of the change (Δ) variables. Table 7 summarizes the full variable space: six rings $\times$ three windows $\times$ four measures yields 72 fire variables.

Table 7: Fire Variable Inventory

Dimension	Levels	Count
Spatial ring radius (km)	5, 10, 15, 20, 25, 30	6
Look-back window (years)	5, 10, 15	3
Fire-activity measure	Fire count, Acreage burned, Δ Fire count, Δ Acreage burned	4
Total fire variables $(6 \times 3 \times 4)$		**72**

Notes: Spatial-ring construction is illustrated in Figure 4; the change (Δ) measures are illustrated in Figure 5.

A.2 FIA Sample Composition: Forest Type and Stand Origin

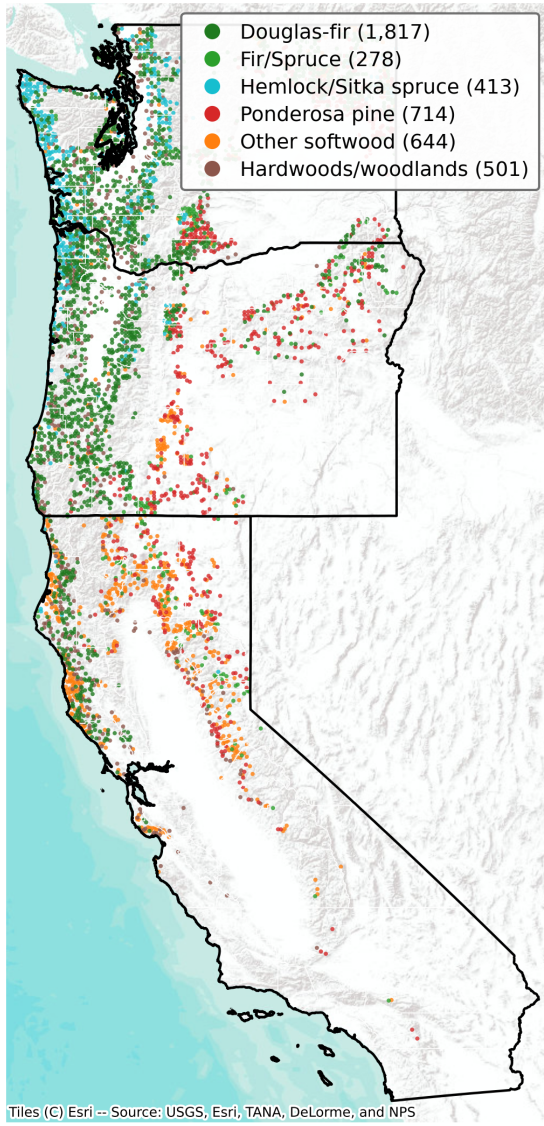

Figure 6: FIA plots by forest type group

Notes: The map shows the same 4,367 unique FIA plots from the harvest-choice estimating sample as in Figure 3, here colored by forest type group. Forest type codes are recorded at FIA measurement. State boundaries shown in black. Basemap: Esri World Terrain.

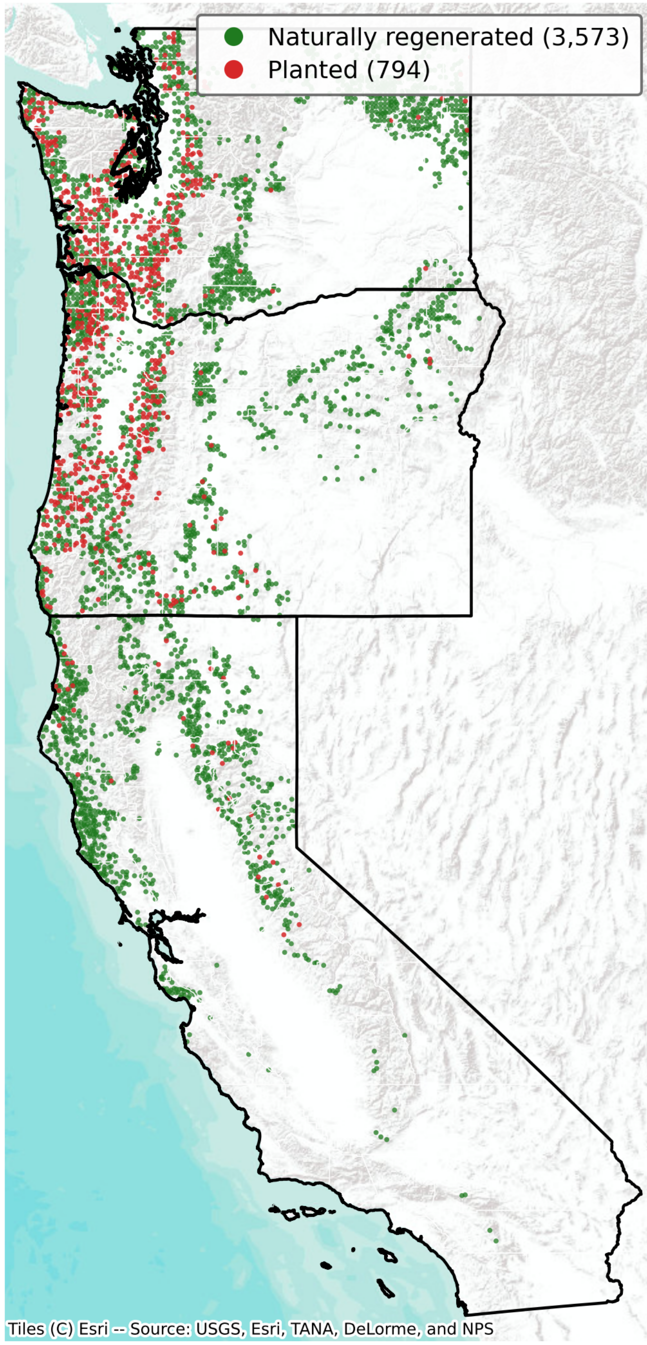

Figure 7: FIA plots by stand origin (planted vs naturally regenerated)

Notes: The map shows the same 4,367 unique FIA plots from the harvest-choice estimating sample as in Figure 3, here colored by stand origin. Stand origin is determined by FIA field crews. State boundaries shown in black. Basemap: Esri World Terrain.

B Stand Density Model: Additional Results

B.1 Robustness Checks

Table 8 reports a set of robustness checks for the planting density specification of Table 3 column 1. All six columns use the same fire variable as the baseline—the 10-year change in fire count within 0-30 km of the plot, lagged to be strictly pre-planting—and vary along three dimensions. Columns (2)-(4) successively drop the stand age (STDAGE) and time-since-planting controls; the coefficient on the fire variable barely moves from the baseline of -0.099 (varying between -0.097 and -0.099) and remains significant at the 1% level in every column, indicating that the headline result does not hinge on these controls. Column (5) replaces the dependent variable with the log of seedling trees per acre for the dominant species; the coefficient is slightly smaller in magnitude (-0.086) but still significant at the 1% level. Column (6) restricts the sample to plantings observed within three years of the planting year, where natural-regeneration and mortality effects between planting and measurement are weakest; the fire coefficient is larger in magnitude (-0.129) and remains significant at the 1% level. The negative effect of recent nearby fire activity on planting density is robust across all six specifications.

Table 8: Stand Density Model: Robustness Checks

	(1) Baseline (Tbl. 3 col. 1)	(2) Drop STDAGE	(3) Drop TSP	(4) Drop both	(5) Seedling TPA (DV)	(6) Subsample TSP $\leq$ 3
Δ Fire count (10-yr), 0-30 km	-0.0987***	-0.0983***	-0.0969***	-0.0963***	-0.0859***	-0.1286***
	(0.0237)	(0.0240)	(0.0223)	(0.0227)	(0.0301)	(0.0404)
Stand age (STDAGE)	Yes	No	Yes	No	Yes	Yes
Time since planting (TSP)	Yes	Yes	No	No	Yes	Yes
Outcome variable	log Planting TPA (dominant species)				log Seedling TPA	log Planting TPA
Sample restriction	Full planted sample				Full planted sample	TSP $\leq$ 3
Site class dummies	Yes	Yes	Yes	Yes	Yes	Yes
Topographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Planting year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	556	556	556	556	475	274
Counties (clusters)	67	67	67	67	62	59
R^2	0.365	0.364	0.351	0.350	0.300	0.567

Notes: Weighted least squares estimates of the planting density model on cumulative wildfire-exposure variables for newly established plantations in OR, CA, and WA. All six columns use the same fire variable as Table 3 column 1: the 10-year change in fire count within 0-30 km of the plot (lagged to be strictly pre-planting). Column (1) reproduces Table 3 column 1. Columns (2)-(4) successively drop the stand age and time-since-planting controls. Column (5) replaces the dependent variable with the log of seedling trees per acre for the dominant species. Column (6) restricts the sample to plantings observed within 3 years of the planting year, where mortality and natural-regeneration concerns are weakest. All specifications include topographic controls (elevation, slope, aspect), site class dummies, 15-year growing-season climate controls (max VPD, precipitation, mean temperature), a post-burn planting indicator, county fixed effects, and planting year fixed effects. Weighted by the condition proportion; standard errors clustered by state-county. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Harvest Choice Models: Additional Results

C.1 Main MNL: Full Coefficient Set

Table 9 reports the full coefficient set for the headline multinomial logit reported in Table 4, including the estimates on stand age, climate controls, period fixed effects, the direct-burn dummy, and the CRE Mundlak group means of each time-varying regressor.

Table 9: Multinomial Logit, Full Coefficient Set: Partial Cut Equation

	Aggregated (0–30 km)		Decomposed (0–5 & 5–30 km)	
	(1) Acreage	(2) Fire count	(3) Acreage	(4) Fire count
Wildfire 0–30 km	0.0044**	0.0762***		
	(0.0019)	(0.0282)		
0–5 km			-0.0218	-0.1851
			(0.0403)	(0.1632)
5–30 km			0.0051**	0.0936***
			(0.0023)	(0.0307)
Wildfire 0–30 km, CRE bar	-0.0102***	-0.1113***		
	(0.0025)	(0.0315)		
0–5 km, CRE bar			0.0026	0.1418
			(0.0544)	(0.1887)
5–30 km, CRE bar			-0.0107***	-0.1285***
			(0.0029)	(0.0345)
Stand age (years)	-0.0071	0.0000	-0.0070	0.0012
	(0.0249)	(0.0245)	(0.0249)	(0.0246)
Stand age, CRE bar	0.0059	-0.0016	0.0058	-0.0028
	(0.0249)	(0.0246)	(0.0249)	(0.0246)
Direct burn	1.2369***	1.4753***	1.3683***	1.6156***
	(0.4102)	(0.3927)	(0.4224)	(0.4072)
Direct burn, CRE bar	0.9179	-0.1503	1.0459	-0.2700
	(1.5734)	(1.6367)	(1.7696)	(1.6678)
15-yr GS Max VPD	0.4426*	0.3746	0.4370*	0.3645
	(0.2532)	(0.2487)	(0.2534)	(0.2482)
Max VPD, CRE bar	-0.3775	-0.3125	-0.3721	-0.3024
	(0.2530)	(0.2483)	(0.2532)	(0.2478)
15-yr GS Precip (mm)	-0.0061	-0.0069	-0.0061	-0.0071
	(0.0066)	(0.0066)	(0.0066)	(0.0066)
Precip, CRE bar	0.0025	0.0032	0.0025	0.0033
	(0.0067)	(0.0067)	(0.0067)	(0.0067)
15-yr GS Mean Temp	-0.9235*	-0.7756	-0.9160*	-0.7505
	(0.5566)	(0.5439)	(0.5560)	(0.5434)
Mean Temp, CRE bar	0.7806	0.6344	0.7734	0.6092
	(0.5567)	(0.5438)	(0.5560)	(0.5434)
Period 2005–08	0.3945	0.3730	0.3935	0.3662
	(0.2402)	(0.2397)	(0.2402)	(0.2396)
Period 2009–12	-0.0137	-0.0812	-0.0141	-0.0934
	(0.2483)	(0.2466)	(0.2483)	(0.2466)
Period 2013–16	0.0158	-0.0591	0.0162	-0.0640
	(0.2620)	(0.2606)	(0.2618)	(0.2608)
Period 2017–24	0.0577	-0.0455	0.0547	-0.0527
	(0.2724)	(0.2695)	(0.2720)	(0.2692)
Constant	-2.9408***	-2.8037***	-2.9417***	-2.7962***
	(0.4190)	(0.4138)	(0.4199)	(0.4137)
Observations	51,451	51,451	51,451	51,451
Plots (clusters)	4,367	4,367	4,367	4,367
Log pseudolikelihood	-4402.3	-4404.5	-4395.0	-4402.3
Pseudo R^2	0.128	0.128	0.130	0.128

Notes: Coefficients from the Partial Cut Equation of the multinomial logit specifications in Table 4; do-nothing is the base outcome. CRE-bar rows are within-unit (Mundlak) means of the corresponding regressor. Period base = 2001–04. Sample, weighting, and SE clustering as in Table 4. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Multinomial Logit, Full Coefficient Set: Clearcut Equation

	Aggregated (0–30 km)		Decomposed (0–5 & 5–30 km)	
	(1) Acreage	(2) Fire count	(3) Acreage	(4) Fire count
Wildfire 0–30 km	-0.0035	-0.0151		
	(0.0032)	(0.0466)		
0–5 km			0.1777***	0.3151
			(0.0602)	(0.2594)
5–30 km			-0.0084**	-0.0361
			(0.0034)	(0.0492)
Wildfire 0–30 km, CRE bar	-0.0030	-0.0761		
	(0.0039)	(0.0610)		
0–5 km, CRE bar			-0.1058	-0.3086
			(0.0928)	(0.3372)
5–30 km, CRE bar			0.0004	-0.0617
			(0.0041)	(0.0645)
Stand age (years)	0.5691***	0.5699***	0.5724***	0.5709***
	(0.0235)	(0.0235)	(0.0236)	(0.0235)
Stand age, CRE bar	-0.5804***	-0.5809***	-0.5837***	-0.5819***
	(0.0237)	(0.0237)	(0.0237)	(0.0237)
Direct burn	3.1035***	2.5211***	1.5735	2.2910***
	(1.1873)	(0.9045)	(1.1248)	(0.8839)
Direct burn, CRE bar	-18.8846**	-17.0229**	-19.7790***	-17.0829**
	(8.0141)	(7.3302)	(6.9922)	(7.1527)
15-yr GS Max VPD	-0.2684	-0.2728	-0.2986	-0.2856
	(0.1981)	(0.2014)	(0.1992)	(0.2029)
Max VPD, CRE bar	0.1736	0.1962	0.2030	0.2095
	(0.2015)	(0.2062)	(0.2026)	(0.2076)
15-yr GS Precip (mm)	-0.0191***	-0.0189***	-0.0191***	-0.0189***
	(0.0039)	(0.0039)	(0.0039)	(0.0039)
Precip, CRE bar	0.0214***	0.0209***	0.0214***	0.0209***
	(0.0038)	(0.0038)	(0.0038)	(0.0038)
15-yr GS Mean Temp	1.7220***	1.7988***	1.7770***	1.8185***
	(0.4523)	(0.4544)	(0.4577)	(0.4574)
Mean Temp, CRE bar	-1.5907***	-1.6865***	-1.6484***	-1.7083***
	(0.4502)	(0.4535)	(0.4553)	(0.4562)
Period 2005–08	-1.2314***	-1.2475***	-1.2359***	-1.2462***
	(0.2456)	(0.2461)	(0.2458)	(0.2463)
Period 2009–12	-2.2051***	-2.2140***	-2.1988***	-2.2094***
	(0.2663)	(0.2652)	(0.2663)	(0.2654)
Period 2013–16	-2.2712***	-2.2874***	-2.2767***	-2.2882***
	(0.2798)	(0.2791)	(0.2801)	(0.2796)
Period 2017–24	-3.5225***	-3.5806***	-3.5355***	-3.5870***
	(0.3108)	(0.3108)	(0.3124)	(0.3115)
Constant	-3.2001***	-3.0500***	-3.1527***	-3.0292***
	(0.4594)	(0.4718)	(0.4538)	(0.4709)
Observations	51,451	51,451	51,451	51,451
Plots (clusters)	4,367	4,367	4,367	4,367
Log pseudolikelihood	-4402.3	-4404.5	-4395.0	-4402.3
Pseudo R^2	0.128	0.128	0.130	0.128

Notes: Coefficients from the Clearcut Equation of the multinomial logit specifications in Table 4; do-nothing is the base outcome. CRE-bar rows are within-unit (Mundlak) means of the corresponding regressor. Period base = 2001–04. Sample, weighting, and SE clustering as in Table 4. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: MNL Robustness: Direct Burn vs. Inner Ring

	Decomposed rings, *no* direct burn			Outer ring only, *with* direct burn		
	(1) Fire count (15-yr)	(2) Acreage burned (15-yr)	(3) Δ Fire count (10-yr)	(4) Fire count (15-yr)	(5) Acreage burned (15-yr)	(6) Δ Fire count (10-yr)
Panel A: Partial Cut vs. Do Nothing						
0–5 km	-0.0321	0.0423	-0.0900			
	(0.1719)	(0.0453)	(0.1078)			
5–30 km	0.0964***	0.0056**	-0.0048	0.0883***	0.0045**	-0.0059
	(0.0309)	(0.0023)	(0.0218)	(0.0301)	(0.0020)	(0.0215)
Direct burn				1.5113***	1.2554***	1.5624***
				(0.3943)	(0.4083)	(0.3954)
Panel B: Clearcut vs. Do Nothing						
0–5 km	0.3065	0.1399***	0.1902			
	(0.2575)	(0.0495)	(0.1209)			
5–30 km	-0.0359	-0.0079**	0.0063	-0.0268	-0.0041	0.0120
	(0.0493)	(0.0033)	(0.0219)	(0.0484)	(0.0032)	(0.0218)
Direct burn				2.5479***	3.1477***	2.4353***
				(0.8989)	(1.1656)	(0.8599)
Observations	51,451	51,451	49,477	51,451	51,451	49,477
Plots (clusters)	4,367	4,367	4,362	4,367	4,367	4,362
Log pseudolikelihood	-4413.8	-4406.9	-4340.2	-4403.7	-4401.9	-4330.4
Pseudo R^2	0.126	0.127	0.120	0.128	0.128	0.122

Notes: Multinomial logit estimates of the harvest-choice model in Table 4 columns 4–6, showing robustness of the decomposed-ring specifications to the direct-burn dummy. Columns (1)–(3) include both the 0–5 km inner ring and the 5–30 km outer ring of the fire variable, but *exclude* the direct-burn dummy. Columns (4)–(6) include only the outer ring along with the direct-burn dummy. The direct-burn dummy equals one when the condition itself burned in either of the two prior years. All specifications include stand age, climate controls, CRE group means of each time-varying regressor, and period fixed effects. Weighted by the t-1 condition proportion; standard errors clustered by plot. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Direct Burn and Inner Ring Robustness

Table 11 reports a robustness check on the decomposed-ring specifications of Table 4 columns 4–6. The published specifications include both the 0–5 km inner ring of the fire variable and a direct-burn dummy equal to one when the condition itself burned in the prior 1–2 years. These two regressors are mechanically correlated, so it is sensible to estimate the same column with one or the other included rather than both. Columns (1)–(3) keep both rings and drop the direct-burn dummy; columns (4)–(6) keep the direct-burn dummy and drop the inner ring. Across both panels, the 5–30 km outer-ring coefficient is largely unchanged between the two versions and across all three fire measures, indicating that the headline outer-ring result is robust to how we handle the inner-ring/direct-burn collinearity.

C.3 Nested Logit Robustness Check

The multinomial logit (MNL) of Section 5 assumes independence of irrelevant alternatives (IIA) across the three management actions. We test this assumption by re-estimating the harvest-choice model as a nested logit on the same sample, with the two harvest actions (partial cut and clearcut) grouped in a "cut" nest above the no-action alternative. The dissimilarity parameter τ_{cut} measures the correlation between the partial cut and clearcut idiosyncratic errors: $\tau_{\text{cut}} = 1$ corresponds to the MNL (full IIA), while $\tau_{\text{cut}} < 1$ indicates that the two cut alternatives share unobserved variation with each other beyond what they share with no action.

Table 12 reports the results. The estimated dissimilarity parameter is $\tau_{\text{cut}} = 0.40$ [95% CI: 0.26, 0.54] in the fire-count specification and $\tau_{\text{cut}} = 0.40$ [95% CI: 0.25, 0.54] in the acreage-burned specification. The Wald test of $H_0 : \tau_{\text{cut}} = 1$ rejects the IIA assumption at the 1% level in both specifications ($\chi^2(1) = 69.4$ and 64.9, respectively, both $p < 0.001$), and the nested logit's log pseudolikelihood is approximately 19 points higher than the MNL's on the same data. The sign of the fire coefficient on the partial cut equation is positive in both the MNL and the nested logit, and the sign on the clearcut equation is negative in both. The qualitative result from Section 6—that elevated regional fire activity shifts landowner harvest behavior away from clearcutting and toward partial cutting—is preserved when we relax the IIA assumption.

Table 12: Nested Logit Robustness Check

	Fire count (15-yr), 0–30 km		Acreage burned (15-yr), 0–30 km	
	MNL (Tbl. 4 col. 1)	Nested logit (this column)	MNL (Tbl. 4 col. 2)	Nested logit (this column)
Panel A: Fire coefficient on the Partial Cut equation				
Fire coefficient	0.0762***	0.0467*	0.0044**	0.0021
	(0.0282)	(0.0267)	(0.0019)	(0.0019)
Panel B: Fire coefficient on the Clearcut equation				
Fire coefficient	−0.0151	−0.0069	−0.0035	−0.0017
	(0.0466)	(0.0329)	(0.0032)	(0.0019)
Panel C: Dissimilarity parameter and IIA test				
Dissimilarity τ_{cut}	—	0.400	—	0.396
		(0.072)		(0.075)
95% confidence interval	—	[0.260, 0.541]	—	[0.249, 0.544]
Wald test $H_0 : \tau_{\text{cut}} = 1$: $\chi^2(1)$	—	69.44	—	64.86
p-value	—	<0.001	—	<0.001
Observations (cases)	51,451	51,451	51,451	51,451
Plot clusters	4,367	4,367	4,367	4,367
Log pseudolikelihood	−4,404.5	−4,385.5	−4,402.3	−4,383.3

Notes: Side-by-side comparison of the multinomial logit (Table 4, columns 1 and 2) and a nested logit on the same sample, same covariates, and same lagged fire variables. The nested logit groups partial cut and clearcut into a "cut" nest above the no-action alternative; the dissimilarity parameter τ_{cut} measures the correlation between the partial cut and clearcut idiosyncratic errors. $\tau_{\text{cut}} = 1$ corresponds to the multinomial logit (full IIA); $\tau_{\text{cut}} < 1$ indicates correlation within the cut nest. The Wald test of $H_0 : \tau_{\text{cut}} = 1$ rejects the IIA assumption at the 1% level in both specifications; the nested logit also achieves a substantially higher log pseudolikelihood than the MNL on the same sample. The headline qualitative result of the harvest-choice analysis is preserved: the fire coefficient on the partial cut equation is positive in both models and both specifications, and the coefficient on the clearcut equation is negative in both. Direct magnitude comparison between the MNL and nested-logit coefficients is not apples-to-apples because the nested logit re-parameterizes the alternative-level utilities relative to τ_{cut}. All specifications include stand age, climate controls, CRE group means, period FE, and a direct-burn dummy. Weighted by the t-1 condition proportion; standard errors clustered by plot. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.4 Partial Cut Timing

Table 13 reports the partial cut timing analysis, which estimates how stand age at the time of partial cut varies with prior nearby wildfire exposure. Conditional on a partial cut occurring, higher local fire exposure shifts the timing earlier in the rotation.

Table 13: Stand Age at Partial Cut and Wildfire Exposure

	0–15 km		Decomp. (0–5, 5–15)		0–30 km		Decomp. (0–5, 5–30)	
	(1) Count	(2) Acres	(3) Count	(4) Acres	(5) Count	(6) Acres	(7) Count	(8) Acres
Wildfire exposure, 0–15 km	-2.3474***	-0.2052*						
	(0.8999)	(0.1069)						
0–5 km			-3.2899	-0.0801				
			(2.9181)	(0.9005)				
5–15 km			-2.0825*	-0.2183				
			(1.2175)	(0.1446)				
Wildfire exposure, 0–30 km					-0.8977*	-0.0521		
					(0.5351)	(0.0445)		
0–5 km							-3.6303	-0.6871
							(2.8934)	(0.7327)
5–30 km							-0.6875	-0.0389
							(0.6121)	(0.0494)
Direct Burn	2.2292	7.5347	2.7181	6.5286	-0.0005	1.3807	1.9589	8.1720
	(6.2451)	(7.5773)	(6.4980)	(10.3493)	(5.9234)	(5.7843)	(6.3404)	(9.5454)
Topographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	534	534	534	534	534	534	534	534
Counties (clusters)	77	77	77	77	77	77	77	77
R^2	0.391	0.389	0.391	0.389	0.389	0.386	0.390	0.387

Notes: OLS estimates of stand age (years) at the time of a partial cut event on lagged wildfire exposure. The sample is FIA partial cut events on private and state timberland in OR, CA, and WA; partial cuts marked as salvage by FIA field crews are dropped. The dependent variable is stand age at the year of the partial cut event; one observation per event. Fire-count specifications (columns 1, 3, 5, 7) count fire events within the indicated radius over the 15 years prior to the event. Acres-burned specifications (columns 2, 4, 6, 8) sum acres burned within that radius and window, in thousands of acres. The aggregated specifications (columns 1, 2, 5, 6) enter exposure as a single regressor; the decomposed specifications (columns 3, 4, 7, 8) split it into a 0–5 km inner ring and an outer ring (5–15 km in columns 3–4, 5–30 km in columns 7–8) entered jointly. Direct Burn is a dummy equal to 1 if the unit's own stand burned 1–2 years prior to the partial cut. Topographic controls are slope, aspect, and elevation. Climate controls are 15-year growing-season averages of max VPD, precipitation, and mean temperature. Standard errors clustered by county. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.5 Pre-Commercial Thinning Results

Table 14 reports the pre-commercial thinning model.

Table 14: Pre-Commercial Thinning and Wildfire Exposure

	Aggregated (0–30 km)			Decomposed (0–5 & 5–30 km)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Fire count	Fire count	Acreage burned	Δ Fire count	Fire count	Acreage burned
Wildfire exposure, 0–30 km	0.0017	0.1366	0.0018			
	(0.0706)	(0.1239)	(0.0028)			
0–5 km				-0.2155	-0.9448	0.0265
				(0.3376)	(0.7684)	(0.0910)
5–30 km				0.0110	0.1528	0.0019
				(0.0694)	(0.1196)	(0.0047)
Stand age (years)	-0.0155	-0.0201	-0.0128	-0.0160	-0.0186	-0.0140
	(0.0521)	(0.0522)	(0.0518)	(0.0520)	(0.0520)	(0.0521)
Climate controls	Yes	Yes	Yes	Yes	Yes	Yes
Group Means	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,450	12,831	12,831	12,450	12,831	12,831
Plots (clusters)	1,258	1,279	1,279	1,258	1,279	1,279
Log pseudolikelihood	-576.1	-587.3	-587.8	-576.0	-585.9	-586.6
Pseudo R^2	0.033	0.034	0.034	0.034	0.037	0.036

Notes: Logit estimates of an annual pre-commercial thinning indicator on condition–year observations for planted stands in OR, CA, and WA with stand age between 6 and 30 years; units that ever had a salvage pre-commercial thinning are excluded. Fire variables are lagged to end the year before the management year. The fire-count specifications (columns 2, 5) count fire events within the indicated radius over the 15-year lookback window; the acreage-burned specifications (columns 3, 6) sum acres burned within that radius and window, in thousands of acres; the Δ fire-count specifications (columns 1, 4) take the 10-year fire count minus the count in the prior decade. The aggregated specifications enter exposure within 0–30 km as a single regressor; the decomposed specifications split it into 0–5 km and 5–30 km rings entered jointly. All specifications include climate controls, CRE group means, and period fixed effects. A direct-burn (1–2 year) indicator is omitted: none of the 146 pre-commercial thinning events in the analytic sample occurs on a stand that experienced a direct burn in the preceding 1–2 years, so the coefficient is not identified. Weighted by condition proportion; standard errors clustered by plot. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Monte Carlo Simulation: Regional Responses

The body reports the harvest-composition and replanting-density results of the Monte Carlo simulation by region in Tables 5 and 6. Figure 8 maps where the four regions lie, and Figure 9 reports the same regional responses as point estimates with 95% cross-iteration intervals.

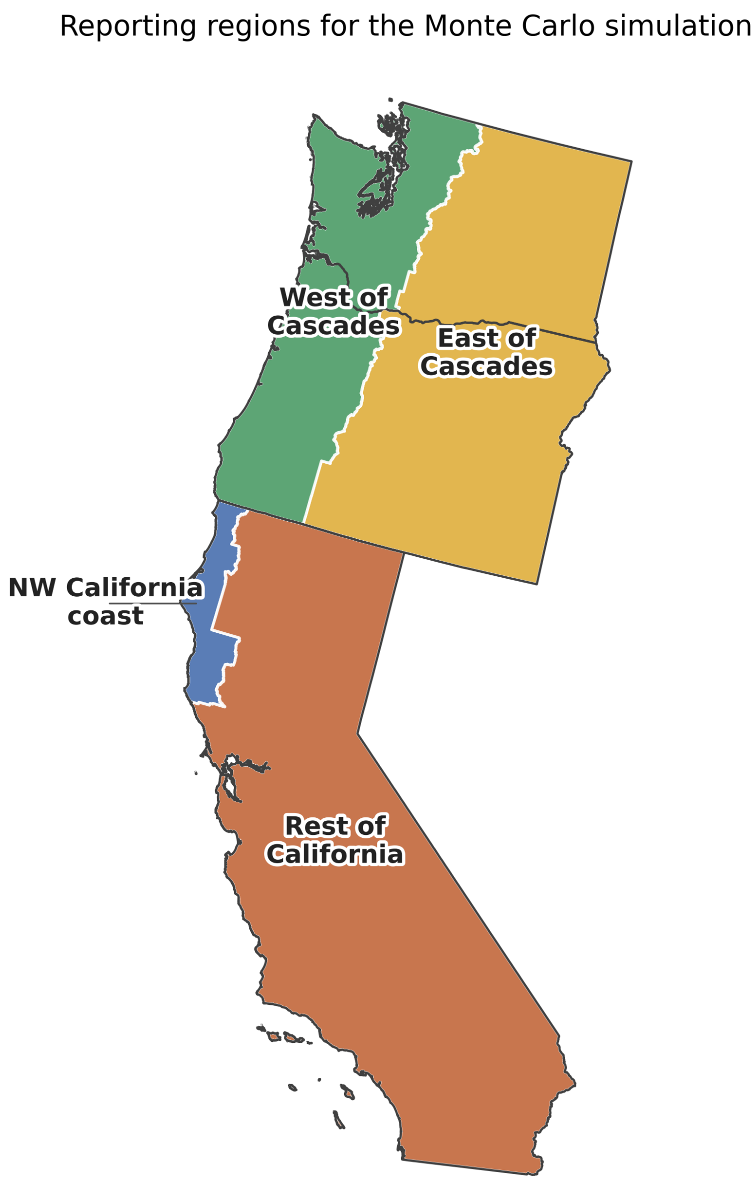

Figure 8: The four reporting regions

Notes: Reference map of the four regions used in Tables 5–6 and Figure 9. "West of Cascades" and "East of Cascades" split the Oregon and Washington counties at the Cascade crest; the NW California coast comprises Del Norte, Humboldt, and Mendocino counties; the rest of California forms the fourth region.

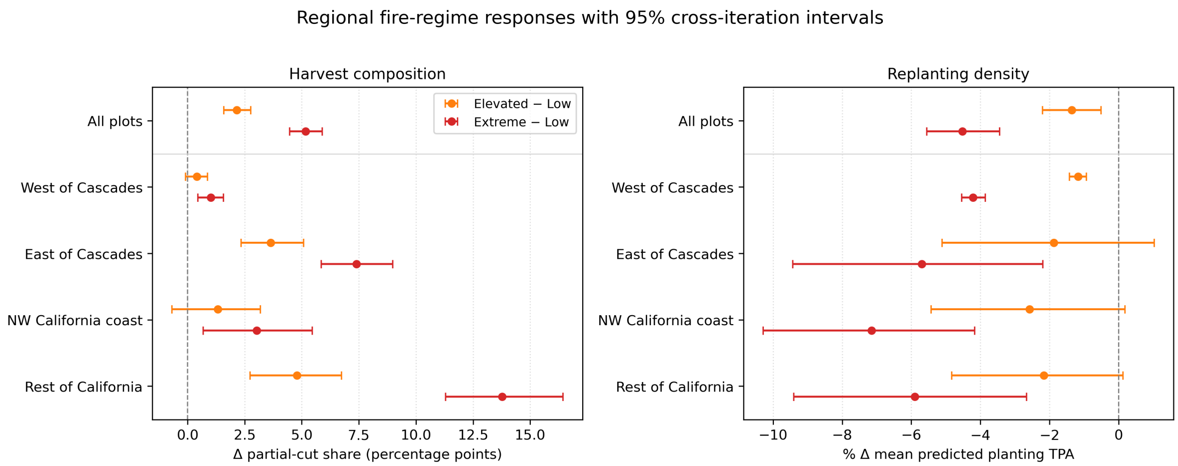

Figure 9: Regional fire-regime responses with 95% cross-iteration intervals

Notes: Each panel plots the full sample and the four regions of Tables 5–6. Markers are point estimates and horizontal bars are 95% cross-iteration intervals (the 2.5th–97.5th percentiles of the 1,000 common-random-number–paired differences). Panel A reports the change in the partial-cut share (percentage points); Panel B reports the percent change in mean predicted planting TPA. Orange markers denote the Elevated−Low contrast and red markers the Extreme−Low contrast. Regions partition the sample: OR/WA west of the Cascade crest, OR/WA east of the crest, the NW California coast (Del Norte, Humboldt, Mendocino), and the rest of California.