Estimating an Economic and Social Value for Healthy Forests: Evidence from Tree Mortality in the American West*

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Abstract

Linkages between healthy forests and human well-being are often theorized, yet the magnitude of benefits remains unknown. This paper uses a natural experiment to assess the welfare consequences of changes in forest health across the American West. My empirical analysis relies on plausibly random variation in tree mortality generated by the thermal threshold at which cold-induced mortality occurs in bark beetles. I find that forest die-off has significant and economically meaningful impacts on both the market value of forests and the non-market benefits these ecosystems provide. I estimate that over the last two decades, tree mortality in the American West decreased the value of timber tracts by $1.1 billion, decreased home values by $16.5 billion, and increased damages from air pollution, wildfire, and floods by a combined $921 million. In a back-of-the-envelope calculation, I find that the death of a tree in my sample costs society $43 in foregone benefits.

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1 Introduction

Trees and forests are valued for tradable goods such as timber, but they deliver other welfare-enhancing services — including air purification, flood regulation, and scenic landscapes — that lack a formal market and are traditionally absent from society's balance sheet. As a result, the magnitude of the benefits that forests provide to humankind remains largely unknown. A common concern is that policy-makers and land managers might undervalue resources that are not quantified, impeding proper management (Costanza et al., 2014). This concern is particularly salient for forests, which face significant challenges to their persistence and health. While forests have long been subject to over-exploitation, recent research suggests that forests have become increasingly vulnerable to climate and associated pest-induced tree mortality events (Allen et al., 2010; Millar and Stephenson, 2015; Van Mantgem et al., 2009). A large ecological literature demonstrates that forest die-off can rapidly alter the size, age, and spatial structure of forests, but the welfare changes assocciated with tree mortality have yet to be quantified (Anderegg et al., 2013).

This study evaluates the impact of tree mortality on the value of forests in the American West. I measure the economic value of forest products that can be harvested and sold in the market using the per acre sales price of publicly owned timber tracts — forested lands for which extraction rights are sold to the highest bidder. To capture non-market value, I use the hedonic pricing method to estimate willingness to pay for the environmental goods and services that trees provide. To further shed light on how tree mortality impacts coupled human–environment systems, I also examine the impact of tree mortality on three dimensions of environmental quality with important welfare implications — air quality improvement, flood mitigation, and wildfire risk. The analysis focuses on tree mortality in particular because the time-varying nature of mortality allows for a uniquely tractable evaluation of the contribution of trees to human well-being. But it is worth noting from the outset that while my results offer new insight into the economic value of forests, tree mortality is only one dimension of forest degradation and its impacts are likely to differ from those of deforestation.

A key challenge in the ecosystem services literature has been establishing causal links between ecosystems and human well-being. In an ideal experiment, the researcher would observe many forests, randomly assign them different levels of tree mortality, and evaluate how these tree mortality "treatments" altered social and economic outcomes. However, it is rarely possible to experimentally manipulate ecosystems at scale. Therefore, existing work primarily determines the effect of changes in forest health on ecosystem services by making assumptions about the equilibrium condition of the forest to use as a reference, by comparing forests to themselves before versus after a mortality event, or by comparing forests affected by tree mortality to an unaffected "control" site. A small collection of observational studies establish negative associations between tree mortality events and ecosystem services such as timber production, recreation, and hazard protection (Thom and Seidl, 2016). However, because these papers do not exploit quasi-experimental conditions, it is not clear whether the relationships they document are causal or correlational.

The primary concern is that the timing and location of forest die-off is likely correlated with other factors that also influence human well-being directly. For example, when using a cross-sectional model to evaluate the impact of Sudden Oak Death on property values in Marin County, California, Kovacs et al. (2011) find that the effect is difficult to identify, with parameter estimates fluctuating between positive and negative across different model specifications. The authors postulate that these results are likely due to the presence of observable characteristics (e.g. soil moisture) correlated with Sudden Oak Death. Because tree mortality is highly dependent on time-varying factors such as temperature and precipitation, which also influence ecosystem services directly, omitted variables bias may persist even when controlling for unobserved differences between locations.

My analysis overcomes this challenge by exploiting a natural experiment where plausibly random variation in tree mortality is generated by differences in pest exposure. Tree mortality is influenced by the interaction of many complex factors, including stand conditions, climate, and exposure to damage agents. Rather than attempting to model all of these pathways simultaneously, this study models just one factor that generates experiment-like conditions: the specific temperature requirements of bark beetles. Bark beetles, which are a leading cause of tree mortality in the American West, are among a class of freeze intolerant insects that cannot withstand the freezing of body tissues. In these species, the supercooling point refers to the temperature at which lethal ice crystals form in the insect tissue (Régnière and Bentz, 2007). I show that in years with more days below the supercooling point, fewer bark beetles survive the winter, resulting in significantly lower levels of tree mortality that summer. Intuitively, this natural experiment allows me to compare a forest to itself in years with similar temperature and rainfall distributions, but in some years the forest is "treated" with one additional day below the supercooling point and thus experiences less tree mortality.

In practice, I compare many different forests to themselves over time using an instrumental variables approach that controls flexibly for potentially confounding climate variables and accounts for unobserved time-invariant factors, such as geography and soil type, as well as state-specific time-trending variables, such as trends in local economic conditions. To implement this approach, I first model cold-induced mortality in bark beetles using an entomological model developed by Régnière and Bentz (2007). This model allows me to generate location-specific estimates of the proportion of bark beetles to survive the winter each year, the instrument used for identification throughout the paper. Next, I establish that there is a strong positive correlation between the instrument and annual tree mortality. Finally, using the plausibly random changes in tree mortality generated by the natural experiment, I estimate the effect of forest die-off on social and economic outcomes.

Under my estimation strategy, a few empirical concerns remain. First, my approach requires the assumption that the instrument I use to generate plausibly exogenous changes in tree mortality does not affect ecosystem service outcomes through a channel other than tree mortality. To test whether the instrument is identifying generic patterns between climate and ecosystem services, I conduct a placebo test that checks for correlations between the instrument and the outcomes of interest in forested areas without bark beetles. Second, the measured benefits may represent a lower bound on the true value of forests if the effects of tree mortality persist over time or there are spatial spillovers in the benefits of healthy trees. I investigate these possibilities using models that include temporal and spatial lags. Third, my natural experiment identifies a local average treatment effect (LATE) — the average effect of tree mortality *caused by bark beetles*. If beetle-induced mortality has a different effect on ecosystem services than other types of tree mortality, the LATE I identify will differ from the "average treatment effect" (ATE) of tree mortality. To probe this possibility, I investigate one critical way in which beetle-caused tree mortality is known to differ from other types of mortality — the degree of spatial clustering in mortality. Finally, it is worth noting that my estimates reflect the effect of tree mortality across all forests in the Western US; however, I recognize forests comprise a diverse set of ecosystems with different capacities to provide goods and services. Future research should investigate heterogeneous effects across forests with different compositions, age structures, stand conditions, and spatial scales.

The remainder of the paper is organized as follows. Section 2 describes the data and instrument construction. Section 3 outlines my empirical approach. Section 4 presents my empirical estimates for the effect of tree mortality on ecosystem services, along with several extensions, and a valuation of forgone benefits. Section 5 discusses these findings and concludes.

2 Data and Instrument Construction

I provide a brief summary of the data sources, variable definitions, and construction of the bark beetle survival instrument here; further details are provided in SI Appendix A. The sample spans the years 1998 to 2018 and includes all forested areas in the Western US (Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming). I restrict my analysis to the this region because bark beetles are most prevalent in western forests.

Forest health. I obtain data on tree mortality from the U.S. Forest Service (USFS) Insect and Disease Survey (IDS), the primary method monitoring the health of the nation's forests (USFS, 2019a). The IDS provides geospatial polygons outlining areas with tree mortality that has occurred in the last 12 months. This information is collected via annual aerial and ground surveys using Digital Mobile Sketch Mapping (DMSM) Systems. I pair the tree mortality polygons with information on the spatial extent of forests from the National Land Cover Database (Homer et al., 2020). Together, these two sources allow me calculate the percent of forest cover affected by tree mortality, which serves as the primary measure of tree mortality used in this analysis.

I complement the tree mortality data with spatial information on the biological range of bark beetles from the Forest Inventory and Analysis (FIA) unit's National Forest Damage Agent Range

Map (USFS, 2019b). The FIA uses ground surveys to estimate the amount of "basal area" (area of land occupied by tree trunks) with damage attributable to bark beetles. While there are many species of bark beetles, only a few cause extensive tree mortality. These "aggressive" species kill either the entire tree or a portion of it during colonization and brood production. This analysis includes the nine aggressive species known to cause extensive tree mortality in the western US: the Douglas-fir beetle, Engraver beetle, Fir engraver, Jeffrey pine beetle, Mountain pine beetle, Roundheaded pine beetle, Spruce beetle, Western balsam bark beetle, and Western pine beetle. Although the Damage Agent Range Map is only available in the cross-section for the year 2012, it allows me to construct a proxy measure for the baseline level of bark beetle prevalence in each location. I define bark beetle prevalence as the percent of total basal area on which bark beetles have been detected.

Economic and social outcomes. I measure the market value of forests using the per acre sales price of timber tracts on public land. I obtain transition-level records from timber auctions conducted by the USFS, the Bureau of Land Management (BLM), and state agencies from the Timber Data Company. These data contain information on the bid prices for each timber tract, as well as detailed attributes of the tract such as location, harvest acres, harvest volume, and estimated logging costs. I determine the price per acre using the winning bids from oral ascending auctions and second-price sealed bid auction, which should, in theory, reflect the buyer's true valuation of the resource.[1] The per acre sales price of timber tracts captures the value of forest products that can be harvested and sold in the market, but does not reflect the amenity and environmental quality benefits of healthy trees because loggers and saw mills only purchase the right to extract resources from public land rather than purchasing the land outright.

To capture non-market benefits, I use the hedonic pricing method to estimate willingness to pay for the amenity and environmental quality benefits of healthy trees (see SI Appendix B.1 for details on the hedonic method). Specifically, I examine capitalization of tree mortality into home values using zip code-level data on the sales prices of single-family residences from Zillow Research. To fur-

[1] There is some evidence of strategic bidding in forest service auctions, even when incentive compatible mechanisms are used (see Athey et al. (2011)). However, the estimated price distortions are quantitatively small (<1% of bid value).

ther probe the environmental quality benefits of forests, I also examine the impact of tree mortality on three environmental services with important welfare implications — air quality improvement, flood mitigation, and wildfire risk. I obtain annual, remotely-sensed measures of particulate matter from the Global Annual PM2.5 Grids Data Set produced by NASA (van Donkelaar et al., 2018), flood damages from the National Flood Insurance Program's (NFIP) Redacted Policies and Claims Data Set (Dombrowski et al., 2019), and wildfire burned area from the Monitoring Trends in Burn Severity program (Eidenshink et al., 2007).

Climate data. Although tree mortality is only measured annually, temperature and precipitation data are required at higher temporal resolution to construct the bark beetle survival instrument and to capture non-linear relationships between climate, tree mortality, and ecosystem services. I use daily temperature and monthly precipitation data from the PRISM Climate Group, which provides gridded observations at 4km resolution (Daly et al., 2008). To preserve inter-annual variability in weather, I bin the daily temperature record into 2°C intervals (e.g. count of days with temperatures between 0°C and 2°C) and control for rainfall over the course of the year using second-order polynomials in monthly precipitation.

Bark beetle cold tolerance model. The instrument used for identification throughout the paper is a location-specific prediction of bark beetle winter survival. I generate the instrument using a cold tolerance model developed by Régnière and Bentz (2007) that describes bark beetle population success as a function of changes in the minimum daily temperature. The model predicts cold-induced mortality when the minimum daily temperature drops below the insect's supercooling point. However, there is strong evidence that supercooling capacity in bark beetles fluctuates over the course of a year. Cold hardening is the dynamic acquisition of cold tolerance in insects through biochemical and physiological processes, and is most often triggered by cold temperatures (Lee Jr, 1989). To reflect this dynamic process, the model is based on a changing proportion of insects in three cold-hardening states: (1) a non cold-hardened, feeding state, (2) an intermediate state in which individuals have voided their gut content and eliminated as many ice-nucleating agents as possible from their body, and (3) a fully cold-hardened state where insects have accumulated a maximum concentration of antifreeze proteins. Cold-induced mortality is estimated using the equation:

$$p(survival)_{c,d} = min\left(p(survival)_{c,d-1}, \sum_{s} \frac{p_{s,c,d}}{1 + exp(-(T_{c,d} - \alpha_{s,c})/\beta_{s,c}}\right) \tag{1}$$

where the dependent variable, $p(survival)_{c,d}$ is the probability of survival on day d in location c. Here, p_s represents the proportion of the insect population in each cold-hardening state (where s is state 1, 2, or 3) and $T_{c,d}$ is the minimum daily temperature. The parameters $\alpha_{s,c}$ and $\beta_{s,c}$ characterize the distribution of supercooling points accross insects in state s. These distributions are described by logistic probability distribution functions found by fitting curves to the observed supercooling points of insects collected in the field by Bentz and Mullins (1999).[2] Thus survival on each day is calculated the probability of survival in all three cold-hardening states, weighted by the proportion of the population in each state. Because mortality is modeled as a selective process, Equation 1 takes the minimum of this value and survival on the previous day.[3]

The level of winter survival for year t is simply the cumulative predicted survival rate on last day of the season, τ,

$$Survival_{c,t} = p(survival)_{c,\tau} \tag{2}$$

This measure represents the proportion of bark beetles that survive the winter and will attack the tree stock in year t. Winter survival is computed at the most granular spatial resolution for which climate data is available, on the 4km resolution PRISM grid. To merge these data with information on social and economic outcomes, which are measured at the zip-code level, I weigh by treed area when aggregating the instrument over grid cells.

The cold tolerance model is illustrated in Figure 1 for a single location and year. Panel A shows minimum daily temperature throughout the season, T_d. Panel B plots the distribution of

[2]Because the supercooling point distribution functions estimated by Régnière and Bentz (2007) are specific to the mountain pine beetle, I re-estimate their parameters to best fit the dominant bark beetle species in each location.

[3]The model assumes individuals in the population are more or less sensitive to cold relative to other individuals, and that their relative positive on the cold-susceptibility scale remains the same over the season. Individuals that survive a given cold event are not redistributed over the entire distribution of cold-resistance (survival on successive days is not independent).

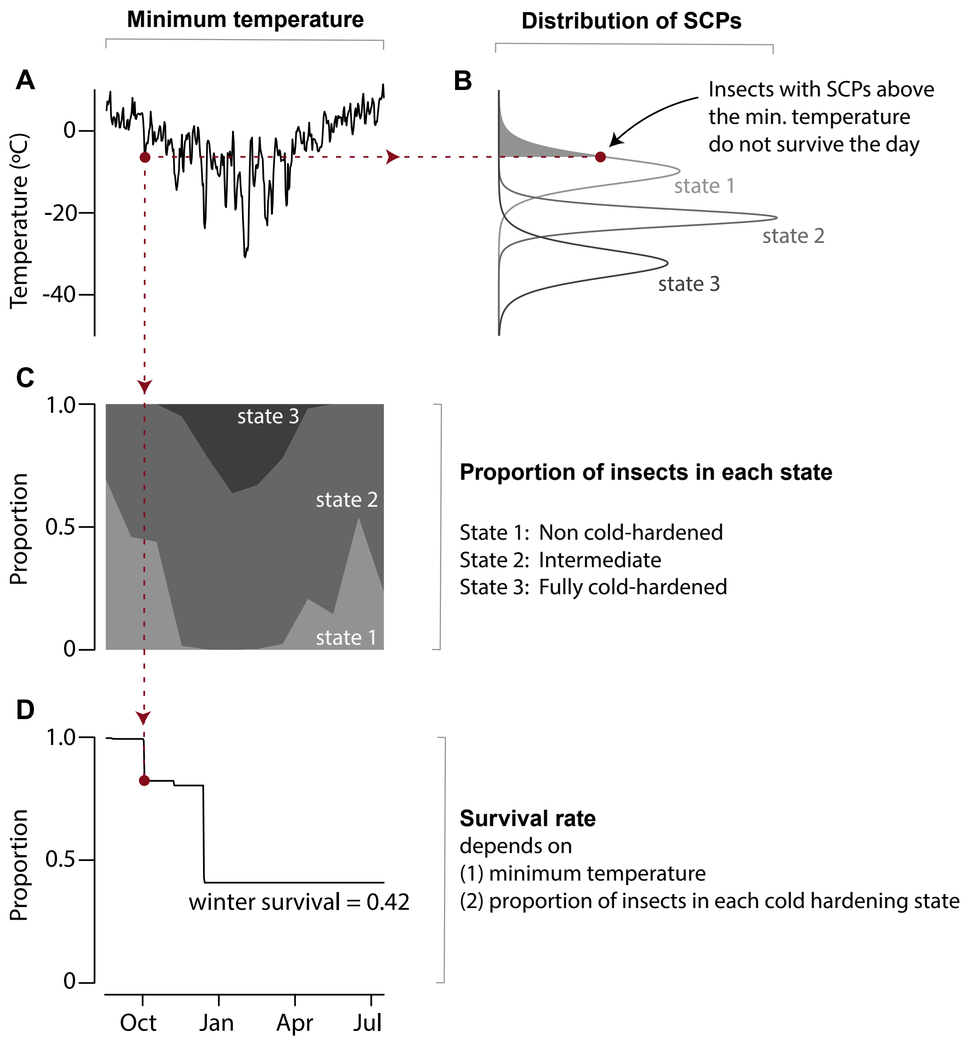

Figure 1: **Model to predict cold temperature-related survival in bark beetles.** I model cold-induced mortality in bark beetles following Régnière and Bentz (2007). See text for details. This figure illustrates how the model is implemented for a single location and year. The model inputs the minimum daily temperature record (A) and determines what proportion of insects have supercooling points below the realized temperature for each day using the distribution of supercooling points (B) across insects in each cold-hardening state. The beetle population transitions through three cold-hardening states over the course of the year (C). Using Equation 1, the model predicts the cumulative proportion of bark beetles to survive each day (D).

supercooling points across insects in each cold-hardening state. Cold-induced mortality occurs when the minimum temperature drops below the supercooling point. Panel C shows the proportion of the population in each cold hardening state, $p_{s,d}$, which is a function of minimum temperature to date. Finally, Panel D shows the cumulative predicted survival rate of the population throughout the year. Thus winter survival is a function of minimum daily temperature (T_t), the proportion of insects in each cold-hardening state ($p_{s,d}$), and the parameters that describe the distribution of supercooling points in each state (α_s and β_s). Intuitively, there are cold-induced mortality events when the minimum daily temperature drops early in the season, before sufficient cold-hardening has occurred, or late in the season, when the beetles have already transitioned back to a feeding state. For example, the dotted red line in Figure 1 shows a day in October where a sudden drop in minimum temperature resulted in large reductions in the survival rate because nearly half of the population was still in a non cold-hardened state.

3 Empirical approach

The goal of my empirical strategy is to capture the causal effect of tree mortality on ecosystem services. The primary challenge is that because tree mortality is not randomly assigned, estimates using standard approaches may be biased by reverse causality or omitted variables. Not only does forest health impact the provision of ecosystem services (what I seek to measure), but society's use of forests also affects the health of these ecosystems. Consider the case of air pollution, for example. It is theorized that trees remove air pollution by the interception of particulate matter on plant surfaces, but there is also evidence to suggest that air pollution puts trees at higher risk of mortality (Dietze and Moorcroft, 2011). Therefore, without exogenous variation in tree mortality, it is not clear whether a positive correlation between tree mortality and air pollution indicates that tree mortality increases air pollution, air pollution increases tree mortality, or the relationship goes in both directions. Furthermore, tree mortality may be correlated with other factors, such as climate or economic development, which also impact ecosystem services directly.

I overcome these challenge by examining changes in tree mortality generated by plausibly random variation in the level of bark beetle survival when the minimum temperature drops below the insect's supercooling point. However, since one might expect a given level of bark beetle winter survival to have different effects in a forest with a low density of bark beetles as opposed to a forest with a high density of bark beetles, I scale the predictions of bark beetle winter survival by the location-specific measure of bark beetle prevalence constructed from the National Damage Agent Range Map.

I implement my empirical strategy using instrumental variables (IV).[4] First, I estimate the impact of bark beetle exposure on tree mortality, using the equation

$$M_{ist} = \pi B_{ist} + \theta \boldsymbol{T}_{ist} + \gamma \boldsymbol{P}_{ist} + \alpha_i + \delta_{st} + \mu_{ist} \tag{3}$$

where M_{ist} is the percent of forest cover affected by tree mortality in zip code i, state s, and year t. Bark beetle exposure, B, is modeled as the interaction between predicted winter survival (the instrument) and bark beetle prevalence (the proportion of basal area on which bark beetles have been detected).[5] In my baseline specification, I model the response as a linear function of bark beetle exposure, but because the functional form of this relationship has minimal precedent in existing literature, I show the robustness of the results to two alternative specifications: piecewise linear and quadratic. To address confounding issues stemming from the relationship between tree mortality and weather, I control flexibly for temperature using 2°C daily temperature bins, $\boldsymbol{T}$, and rainfall using second-degree polynomials in monthly precipitation, $\boldsymbol{P}$. I account for unobservable differences in average levels of tree mortality between locations using zip code fixed effects, α, which might arise, for example, because of different geographies or soil types. I also account for common nonlinear trends in tree mortality and year-specific common shocks within each state using state-year fixed effects δ. I assume that the disturbance term, μ_{ist}, may exhibit spatial correlation as well as autocorrelation within a location over time. To account for this, I estimate standard errors

[4] See SI Appendix B.2 for details on the instrumental variables research design.

[5] This approach resembles a Bartik-like (shift-share) instrument because I interact a plausibly exogenous, time-varying instrument with a potentially endogenous, cross-sectional measure of exposure. However, my approach is not subject to the same concerns about Bartik instruments raised in Goldsmith-Pinkham et al. (2020). In particular, since the winter survival instrument varies not only by time period but also by zip code, the exogenous variation generated by the instrument is preserved and the instrument does not simply act as a weighting matrix for the potentially endogenous exposure measure. Further, the inclusion of zip code fixed effects in the regression controls for cross-sectional differences in bark beetle prevalence.

that are clustered in two dimensions (Cameron et al., 2011): within state-by-years and within zip codes.

The parameter of interest is π, which describes the response of tree mortality to bark beetle exposure. In the IV approach, Equation 3 allows me to generate plausibly exogenous changes in tree mortality caused by changes in bark beetle survival at the supercooling point. However, the estimate of π is also of direct interest to forest resource managers because it quantifies the change in tree mortality that can be expected in response to a marginal increase in bark beetle exposure.

Next, I estimate the impact of tree mortality on ecosystem services using the equation

$$Outcome_{ist} = \beta M_{ist} + \gamma_1 \boldsymbol{T}_{ist} + \gamma_2 \boldsymbol{P}_{ist} + \alpha_i + \delta_{st} + \epsilon_{ist} \tag{4}$$

where $Outcome_{ist}$ is one of the ecosystem service outcomes and all other variables are defined as in Equation 3. I specify the dependent variable in levels for the value of timber tracts, such that a one unit increase in the percent of forest cover with tree mortality changes the price per acre of timber tracts by β dollars. Because process-based ecological models suggest that tree mortality is most likely to have a multiplicative effect on environmental services (Thom and Seidl, 2016), all other dependent variables are log-transformed.[6] For example, the dependent variable in the hedonic regression is the log mean value of homes in zip code i, such that a one unit increase in the percent of forest cover with tree mortality changes the home values in zip code i by β percent. For this part of the analysis, I limit my sample to zip codes in which bark beetles have been detected since the instrument does not generate variation in tree mortality in forests without the pest. As in Equation 3, standard errors are clustered two ways, by state-year and zip code.

My instrumental variables approach requires two assumptions. First, the instrument must capture some of the variation in tree mortality, conditional on covariates. This assumption can be directly tested by examining the parameter estimate of π in Equation 3. The second assumption is that the instrument does not affect ecosystem service outcomes through a channel other than tree mortality. Although this assumption can never be directly tested, I conduct a placebo test

[6]For example, the mechanism through which trees remove air pollution is the interception of particulate matter on plant surfaces, thus the air pollution benefits of trees depend on the baseline level of pollution.

that checks whether the instrument has an effect on ecosystem service outcomes in forested areas without bark beetles. A null effect of the instrument in areas without bark beetles provides us with confidence that the instrument is not simply picking up general correlations between climate (or another unobserved factor) and ecosystem services.

4 Results

Predictions of bark beetle winter survival. I first generate location-specific predictions of the proportion of bark beetles that survive the winter each year. The level of cold-induced mortality predicted by this model in relation winter temperatures is in good agreement with numerous field and laboratory studies of bark beetle species found in the American West (Bentz and Mullins, 1999; Cole, 1981; Safranyik, 1998). To provide a useful point-wise summary statistic, Figure 2A plots the average (across years) winter survival in all forested areas. There is considerable regional heterogeneity in winter survival, with lower rates in the Rocky Mountain region, where the temperature frequently drops below the supercooling point, and higher rates in the milder climate of the Sierra Nevada. Critically for the empirical analysis that follows, there is also substantial variation in winter survival within a location over time. The standard deviation (SD) in winter survival over the years 1998 to 2018 is 21 percentage points, on average across locations. As an example, panels B and C of Figure 2 of plot the time series predictions for two forests: Sierra National Forest in California and Bridger-Teton National Forest in Wyoming. While predicted winter survival rates in California are consistently higher than those in Wyoming, my empirical strategy does not compare forests across these two locations; rather, I compare the Bridger-Teton National Forest to itself in years with relatively low versus high predicted survival rates (e.g. 2007 vs. 2010), while controlling flexibly for potentially confounding climate factors.

The effect of bark beetle winter survival on tree mortality. I find that bark beetle exposure has a strong positive effect on annual tree mortality. At the mean level of bark beetle prevalence (6.6%), I estimate that a one percentage point increase in winter survival increases the percent of forest cover affected by tree mortality by 0.016 (95% confidence interval [CI] = 0.013 to 0.018)

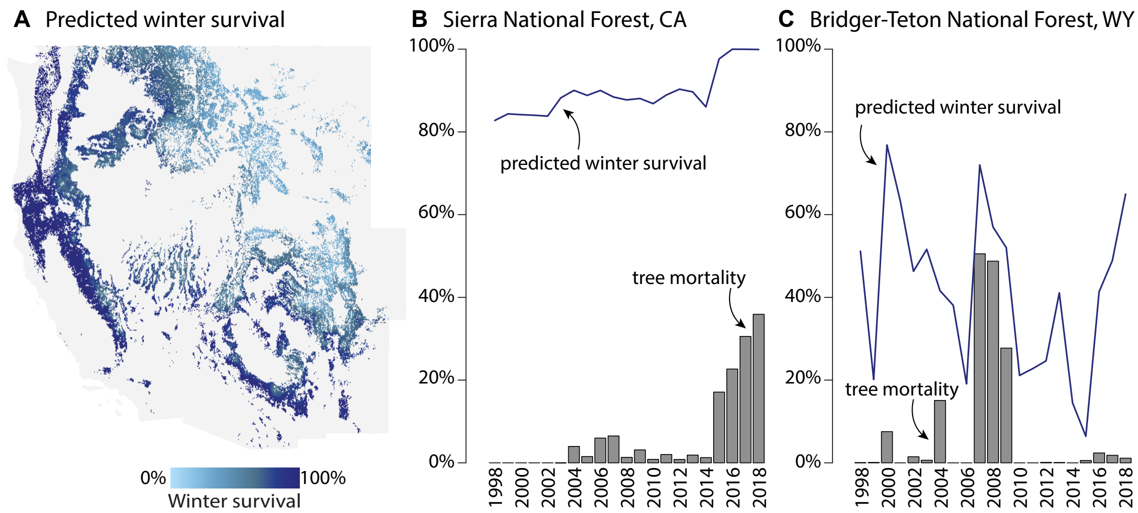

Figure 2: **Predictions of bark beetle winter survival.** I predict the proportion of bark beetles to survive the winter on a 4km grid. (A) The average (across years) predicted winter survival rate at each location. (B) and (C) show examples of variation in the predicted survival rates over time for locations in the Sierra National Forest and Bridger-Teton National Forest.

percentage points (Figure 3B). This amounts to a 21% increase in tree mortality per SD increase in predicted winter survival. Estimation of the response function using more flexible functional forms suggests that assuming a linear model is appropriate in this context. As a placebo test, I also estimate the effect of winter survival in forests without bark beetles. Reassuringly, I do not find an identifiable effect of predicted winter survival outside of the pest's known range, suggesting that the instrument is not simply picking up generic patterns between climate and tree mortality.

Next, I evaluate how the relationship between winter survival and tree mortality depends on the baseline level of bark beetle prevalence in a forest. As expected, the marginal effect of winter survival is increasing in bark beetle prevalence (Figure 3C). For example, I estimate that a one percentage point increase in winter survival increases tree mortality by 0.007 (CI = 0.003 to 0.011) percentage points at the first quartile of beetle prevalence (where beetles have been detected on 3% of basal area) versus 0.034 (CI = 0.025 to 0.043) percentage points at the third quartile of beetle prevalence (where beetles have been detected on 12% of basal area). In the baseline specification, I restrict the effect of winter survival to scaling linearly with beetle prevalence, but using a non-parametric,

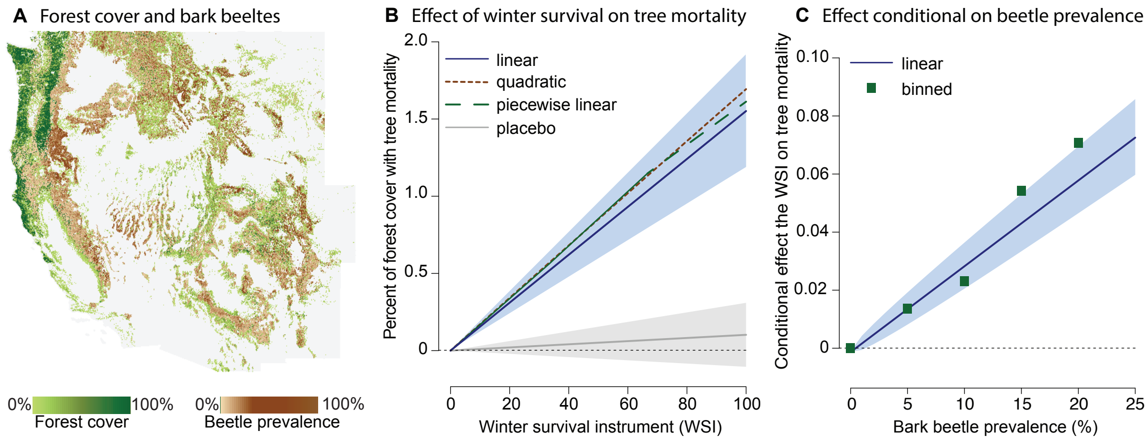

Figure 3: **Effect of bark beetles on tree mortality.** (A) shows the geographic distribution of forests in the American West (green scale), overlaid with a map of bark beetle prevalence (brown scale). Bark beetle prevalence is defined as the proportion of total basal area with damage from bark beetles. (B) plots the estimated effect of bark beetle winter survival on the percent of forest cover with tree mortality for a location with the mean level of bark beetle prevalence (6.6%). I show three functional forms assumptions: linear (blue), quadratic (brown), and piecewise linear (green). The placebo (grey) shows the estimated effect of winter survival in forests without bark beetles. (C) plots the marginal effect of winter survival on tree mortality (y-axis) conditional on bark beetle prevalence (estimated from the interaction terms in equation 8 using OLS). The Shaded polygons show 95% confidence intervals. Standard errors are clustered at two ways by state-year and zip code.

binned approach to estimate the conditional effect yields similar results.

In sum, the effect of bark beetles on tree mortality depends strongly on the interaction between the baseline prevalence of beetles within a forest and annual variations in temperature suitability that determine short-term population success. These first stage results, reported for each subset of the sample in Table A3, provide support for identifying assumption of the IV estimator that requires the instrument to capture significant variation in tree mortality.

Reduced-form estimates of the effect of bark beetles on ecosystem services. Quantifying the effect of bark beetles on ecosystem services has important implications for forest management, but remains an open question in the literature because there is limited information on spatial and temporal patterns of bark beetle exposure (Morris et al., 2017). A key benefit of generating predictions of bark beetle winter survival is that it allows for the empirical estimation of this relationship. Panel A of Table 1 reports the estimated effects off bark beetle exposure on ecosystem services. Recall that bark beetle exposure is defined as the interaction between predicted winter survival and proportion of forested area on which bark beetles have been detected. Thus the coefficient estimates reported in Table 1 can be interpreted as the effect of one percentage point increase in bark beetle survival in a forest that is fully saturated with bark beetles. However, on average, bark beetles have only been detected on 6.6% of basal area; therefore, the estimates should need to be multiplied by 0.066 to be interpreted as the marginal effect of a one percentage point increase in bark beetle winter survival in the average forest.

In the average forest, I estimate that a one percentage point increase in winter survival reduces the price of timber tracts by 3.9 dollars per acre. The effect of beetle exposure on the volume of timber available for harvest is negative and not significantly different from zero, indicating that the price decline cannot be explained by forest managers increasing the supply of timber in the wake of beetle outbreaks by opening up additional tracts for salvage logging. Rather, this finding suggests that wood quality is diminished by beetle-induced mortality. Indeed, if beetle-killed logs are not harvested shortly after mortality, they are more prone to reduced moisture content, checking, blue stain, and rot (Lewis and Hartley, 2006), all of which may reduce their market value.

I also find a negative and significant impact of beetle exposure on local home values, estimating that a one percentage point increase in winter survival reduces local home values by 0.002 percent at the mean level of bark beetle prevalence. This finding suggests that bark beetles are an disamenity that potential homeowners are willing to pay to avoid. The negative impact may in part be explained by declines in the aesthetic value of forests, as the needles of beetle-killed trees turn red and then drop following infestation. Additionally, beetle exposure may affect home values by negatively impacting environmental services, such as hazard protection. Consistent with this hypothesis, I find that bark beetle exposure increases air pollution levels, flooding damages, and wildfire risk.

	Dependent variable:											
	Timber tract value		Timber tract volume		Log mean home value		Log particulate matter		Log flood damages		Log wildfire area	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A:												
Bark beetle exposure	-61.7^{**}	-59.1^{**}	-298.1	-343.8	-0.037^{***}	-0.036^{***}	0.022^{***}	0.022^{***}	0.190^{**}	0.174^{*}	0.055^{*}	0.056*
	(30.4)	(28.1)	(719.3)	(624.9)	(0.007)	(0.007)	(0.005)	(0.004)	(0.095)	(0.095)	(0.028)	(0.027)
Panel B:												
Tree mortality	-249.7^{**}	-250.0^{**}	$-1,122$	$-1,450$	-0.153^{***}	-0.149^{***}	0.110^{*}	0.108^{**}	0.812^{**}	0.746^{*}	0.277^{***}	0.235^{**}
	(116.0)	(118.9)	(3,987)	(3,967)	(0.049)	(0.048)	(0.058)	(0.055)	(0.380)	(0.384)	(0.101)	(0.102)
Climate controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9,817	9,817	9,817	9,817	17,953	17,953	37,240	37,240	37,240	37,240	37,240	37,240
First-stage F-statistic	83.4	83.4	83.4	83.4	69.6	69.6	130.9	. 130.9	130.9	130.9	130.9	130.9
Dep. variable mean	6,619	6,619	21,158	21,158	223,084	223,084	5.47	5.47	7,732	7,732	3.65	3.65

Table 1: **Effect of forest health on ecosystem services.** Panel A reports the reduced-form estimates of the effect of bark beetle exposure on ecosystem services. Panel B reports the IV estimates of effect of tree mortality on ecosystem services. Dependent variables are listed above the columns. Timber tract value is reported in price per acre and timber tract volume is reported in thousand board feet (Mbf). All other dependent variables are log-transformed and the coefficient estimates for columns (5-12) have been multiplied by 100 for demonstration purposes. All regressions include zip code and state-year fixed effects. Standard errors (in parentheses) are clustered by zip code and by state-year. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

The causal effect of tree mortality on ecosystem services. I find that forest die-off has significant and economically meaningful impacts on both the market value of forests and the non-market amenity and environmental quality benefits these ecosystems provide (Table 1, Panel B). I estimate that a one percentage point increase tree mortality reduces the price per acre of timber tracts by \$250; this amounts to a 8% decline in the value of timber tracts per standard deviation increase in annual tree mortality. As with bark beetles, the effect of tree mortality on the volume of timber available for harvest is negative and not significantly different from zero, indicating that the price decline cannot be explained by an excess supply of timber after forest die-off events. My results imply that even in the short-term, timber production losses are not offset by salvage logging after a mortality event. Importantly, the damages to timber tract values caused by tree mortality have direct implications for the welfare of local residents, as timber revenues are traditionally allocated to funding local forest management activities, schools, and road projects.

I also find a strong negative effect of tree mortality on local property values, estimating that a one percentage point increase tree mortality reduces mean home values by 0.15 percent. In terms of magnitude, this finding is broadly consistent with case studies in California and New England that find property values decline by $3-6\%$ in neighborhoods with extensive mortality (Homer et al., 2020; Kovacs et al., 2011). To shed light on potential channels through which tree mortality may capitalize into property values, I also examine the effect of tree mortality on three dimensions of environmental quality that have been shown to influence home values in other contexts — air quality, flood risk, and wildfire burned area. I find that tree mortality reduces the hazard protection value of forests for all three services. I estimate that a one percentage point increase in tree mortality increases ambient PM2.5 concentrations by 0.11 percent, or 0.006 micrograms per cubic meter in the average zip code. This finding is consistent with the predictions of process-based simulations that model the interception and removal of fine particulate matter by tree surfaces (Beckett et al., 1998). Additionally, I estimate that tree mortality increases damages from flooding by 0.75 percent and wildfire burned area by 0.24 percent. While the mechanisms through which tree mortality increases water flows and increases the quantity of fuel available for combustion are well-studied (Bearup et al., 2014; Stephens et al., 2018), these estimates provide new empirical evidence on the real-world response of natural disaster damages to tree mortality in the America West.

The estimates reported here are robust to excluding controls for temperature and precipitation (Table 1), using an alternative definition of tree mortality (SI Appendix, Table A4) and more flexible functional form assumptions (SI Appendix, Figure A3). The estimated effects are also insensitive the withholding of regional blocks of data (SI Appendix, Figure A4), indicating that my results are not driven by one forest or die-off event in particular. In the sections that follow, I expand on my baseline results by testing for the presence of temporal and spatial lags, conducting a placebo test in forested areas without bark beetles, and examining one well-established way in which tree mortality caused by bark beetles differ from other types of tree mortality.

Effect of tree mortality over time and space. The effects estimated using Equation 4 and reported in Table 1 represent the contemporaneous effect of tree mortality in a given zip code on the social outcomes in the same zip code. However, it is possible that the effects of tree mortality persist over time or there are spatial spillovers. I investigate these possibilities by including temporal and spatial lags of tree mortality in the regression model. I estimate the model

$$Outcome_{ist} = \sum_{k=1}^{\kappa} \beta_k M_{kist} + \sum_{k=1}^{\kappa} \gamma_{1k} \boldsymbol{T}_{kist} + \sum_{k=1}^{\kappa} \gamma_{2k} \boldsymbol{P}_{kist} + \alpha_i + \delta_{st} + \epsilon_{kist} \tag{5}$$

where $k = 1, \ldots, \kappa$ indicates either a set of spatial or temporal lags. As in the rest of the analysis, the endogenous tree mortality variable is instrumented for using bark beetle exposure.

In the model with temporal lags, I simultaneously estimate the effect of tree mortality on ecosystem services in the year of the mortality event, as well as in the year preceding and up to three years following the event. This allows me to evaluate how the effect of tree mortality evolves over time, as the effect of tree mortality that occurred one year ago is allowed to differ arbitrarily from the effect of of tree mortality that occurred this year. It also provides a simple robustness check on my identification strategy, as we should expect a null effect of future tree mortality (e.g. tree mortality that occurs in the year 2000 should not effect ecosystem services in the year 1999). In the spatial distributed-lag model, I include spatial lags with a width of 20 kilometers (km) out to a maximum distance of 100 km. Once again, all spatial effects are estimated simultaneously such

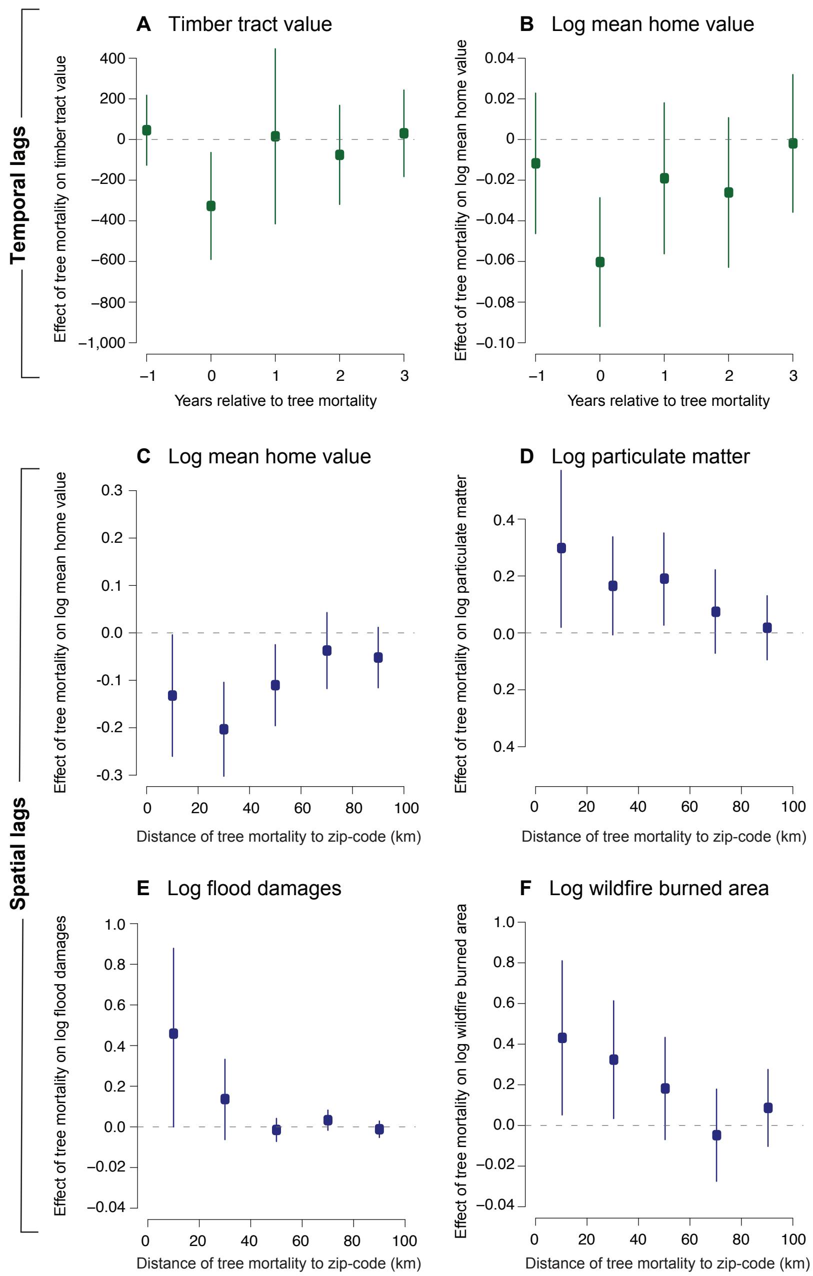

Figure 4: **Models with temporal and spatial lags**. (A) and (B) show the effect of temporal lags of tree mortality on timber tract values (measured in price per acre) and log mean home values, respectively. Years relative to tree mortality is shown on the x-axis, such the point estimate located at x=1 can be interpreted as the effect of tree mortality that occurred one year in the past. (C-F) show the effect of spatial lags of tree mortality on log mean home values, log PM2.5 concentrations, log flood damages as measured by NFIP claims, and log wildfire burned area, respectively. Distance of tree mortality to the zip code is shown on the x-axis in 20km wide bins (e.g. tree mortality 20-40km away from zip code i). All regressions include flexible controls for temperature and precipitation, as well as zip code and state-year fixed effects. Whiskers shown 95% confidence intervals where standard errors are clustered two ways by state-year and zip code.

that the regression equation controls for local levels of tree mortality.

I do not find evidence that the consequences of tree mortality for ecosystem services persist over time, with the estimated effects returning to zero within three years (Figure 4A-B). It is possible that in diverse forests, the loss or reduction in density of one species may be quickly compensated for by other species filling the gap (Boyd et al., 2013; Hessburg et al., 2000). Indeed, moderate tree mortality has been shown to increase understory growth and species richness in the following seeason (Dhar and Hawkins, 2011; Stone and Wolfe, 1996). In Appendix C.4, I investigate whether there is evidence of such regrowth in my data by examining how the normalized difference vegetation index (NDVI) — a simple indicator of live green vegetation — is affected by past tree mortality. I find that while NDVI drops sharply in the year of a tree mortality event, the indicator rebounds to pre-mortality levels within three years. This rapid regrowth may offset the the negative impacts of tree mortality on some ecosystem services, such as the aesthetic value of forests.

In contrast, the models that includes spatial lags of tree mortality do provide evidence of spatial spillovers. For example, I find negative effects on home values for tree mortality out to a distance of 60 kilometers (Figure 4C). This finding is implies that home owners are not only affected by dead trees in their immediate neighborhood, but also by dead trees in the surrounding areas and nearby woodlands. An examination of the spillover effects of tree mortality on the three environmental services provides additional support for the theory that tree mortality has negative spatial externalities (Figure 4D-F).

Placebo Test. The main threat to the validity of the analysis is that the instrument is picking up climate factors that affect ecosystem services through a channel other than bark beetle-induced tree mortality. As a placebo test, I check whether the instrument impacts ecosystem services in forests without bark beetles (i.e. forests in which no basal area loss attributable to bark beetles has been detected). If my identifying assumption holds, the marginal effect of an increase in the instrument, conditional on covariates, should be negligible except when interacted with a dummy for bark beetle presence. The estimating equation for the placebo test is

$$Outcome_{ist} = \pi_1 Survival_{ist} + \pi_2(Survival_{ist} \times I_i^{Beetles}) + \theta I_i^{Beetles} + \gamma_1 \boldsymbol{T}_{ist} + \gamma_2 \boldsymbol{P}_{ist} + \alpha_i + \delta_{st} + \nu_{ist} \tag{6}$$

where $I^{Beetles}$ is a dummy variable for zip codes in which bark beetles have been detected. In Equation 6, the instrument enters as the main effect, but the impact of bark beetle winter survival is identified as the interaction between the dummy variable for areas with bark beetles and the instrument. All other covariates from Equation 4 are included.

Results from the placebo test are shown in Table 2. The second row shows the differential effect of the instrument in areas with bark beetles. The coefficient on the interaction term, $Survival \times \mathrm{I}^{Beetles}$, always has the expected sign is statistically significant for four of the five outcomes. The first row represents that effect of the instrument in areas without bark beetles. The coefficient estimates are all at least an magnitude smaller than the interaction term and none are significantly different from zero. These findings provide evidence that instrument is impacting ecosystem services through beetle-induced tree mortality rather than capturing the effects of an unobserved factor on ecosystem services. Finally, the third row is the sum of the first rows columns, and represents the total effect of the instrument in areas with bark beetles. Consistent with the main analysis, higher predicted bark beetle survival reduces the value of timber tracts and home values, while increasing hazard risk from air pollution and flood damages.

One limitation to this placebo test is that forests with bark beetles do differ from those without the pest in some respects. Most notably, forests with beetles have, on average, significantly more forested area and higher levels tree mortality (Table A5). However, the the ecosystem service outcomes I evaluate are comparable across the two samples (with the exception of wildfire) and the temperature and rainfall distribution in both groups share a common support (Figure A6).

Heterogeneity based on the spatial distribution of tree mortality. The core benefit of my natural experiment is that it allows for the identification of a causal effect. However, this approach identifies a local average treatment effect (LATE) — the average effect of tree mortality *caused by*

	Dependent variable:				
	Timber tract value	Log mean home values	Log PM2.5	Log flood damages	Log wildfire burned area
	(1)	(2)	(3)	(4)	(5)
Forests without beetles	-0.0661	-0.0004	-0.00005	-0.00004	0.0003
(π_1)	(1.971)	(0.0004)	(0.00005)	(0.0006)	(0.0004)
Beetles interaction	-1.766^{*}	-0.0014^{***}	0.0021^{***}	0.0150^{**}	0.0025
(π_2)	(0.834)	(0.0005)	(0.0006)	(0.0068)	(0.0032)
Forests with beetles	-1.832^{*}	-0.0014^{***}	0.0021^{***}	0.0150^{**}	0.0027
($\pi_1 + \pi_2$)	(0.897)	(0.0005)	(0.0006)	(0.0068)	(0.0032)
Observations	15,925	28,831	59,736	59,736	59,736

Table 2: **Placebo Test: The effect of winter survival in forests with and without bark beetles**. OLS estimates of equation (6). Timber tract value is reported in US dollars per acre. All other outcomes are log-transformed, and the coefficient estimates have been multiplied by 100 for demonstration purposes (so the reported value can be interpreted as the percentage point change in the outcome for a one percentage point increase in winter survival). All regressions control flexibly for weather and include zip code and state-year fixed effects. Standard errors (in parentheses) are clustered by zip code and by state-year. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

bark beetles. It is possible that beetle-induced mortality has a different effect on ecosystem services than other types of tree mortality. Although I cannot directly test for this type of heterogeneity because the effect of tree mortality from other causes is not identifiable, I can investigate at least one way in which beetle-induced mortality is different. It is well-established that tree mortality caused by bark beetles exhibits a higher degree of spatial clustering than tree mortality from drought or heat stress (Meddens et al., 2012). If tree mortality that is spatially clustered is more damaging to ecosystem services than the same number of dead trees distributed over a larger area, then the LATE identified by my empirical approach is likely to be different from the the "average treatment effect" (ATE) of tree mortality from all causes.

I test whether the effect of tree mortality on ecosystem services depends on its spatial distribution by implementing a variation of Equation 4 that uses Moran's I to summarize the spatial structure of tree mortality within each zip code. First, I impose a grid structure on the mortality polygons from the IDS data such that I have a 1km $\times$ 1km grid with measures of area affected by tree mortality. Next, I calculate Moran's I for tree mortality in each zip code i and year t using the following equation

$$I_{it} = \frac{N}{\sum_j \sum_k w_{jk}} \times \frac{\sum_j \sum_k w_{jk}(M_j - \bar{M})(M_k - \bar{M})}{\sum_j (M_j - \bar{M})^2}$$

where j and k index grid cells in zip code i. Here, N is the number of grid cells in zip code i, M_j is tree mortality in grid cell j, $\bar{M}$ is the mean tree mortality (across grid cells) in zip code i, and w_{jk} is a matrix of spatial weights with zeros on the diagonal where the weights decrease linearly with distance. The estimating equation is

$$Outcome_{ist} = \beta_1 \hat{M}_{ist} + \beta_2(\hat{M}_{ist} \times I_{ist}) + \theta \boldsymbol{T}_{ist} + \gamma \boldsymbol{P}_{ist} + \alpha_i + \delta_{st} + \epsilon_{ist} \tag{7}$$

where I_{ist} is the Moran's I statistic described above and all other variables are defined as in Equation 4. Note that β_1 is the main effect of tree mortality and β_2 is the differential effect of tree mortality based on its spatial distribution. As in the main analysis, tree mortality is instrumented for with bark beetle exposure. I_{ist} is positive when tree mortality is spatially clustered, zero when it is randomly distributed, and negative when it is dispersed across space. Thus, if β_2 has the same sign as β_1, this implies that spatial clustering in tree mortality increases damages from tree mortality. In contrast, if the two coefficients have opposite signs, it indicates that spatial clustering dampens the negative effect of tree mortality on ecosystem services.

The results are shown in Table 3. There is no clear pattern in whether β_1 and β_2 have the same or opposite signs, and none of the coefficient estimates for β_2 are statistically significant from zero. Thus I do not find evidence that spatial clustering in tree mortality increases or decreases damages from tree mortality for any of the ecosystem service outcomes. Note that while the magnitude of β_2 appears large in relation to β_1 for flood and wildfire risk, more than 95% of observations with positive values of tree mortality have values for I in the range of -0.25 to 0.25; therefore, the differential effect of tree mortality based on spatial correlation rarely overshadows the main effect of tree mortality.

	Dependent variable:				
	Timber tract value	Log mean home values	Log PM2.5	Log flood damages	Log wildfire burned area
	(1)	(2)	(3)	(4)	(5)
M_{ist} (β_1)	-239.7^{**}	-0.14^{***}	0.11^{**}	0.71^{***}	0.22^{**}
	(113.4)	(0.05)	(0.03)	(0.23)	(0.09)
$M_{ist} \times I$ (β_2)	11.7	-0.07	-0.001	0.52	-0.77
	(17.8)	(0.13)	(0.002)	(0.93)	(0.56)
Observations	9,817	17,953	37,240	37,240	37,240

Table 3: **Heterogeneity based on the spatial distribution of tree mortality.** I test whether the effect of tree mortality depends on its spatial distribution by re-running Equation 4 but this time including an interaction between tree mortality and a measure of the spatial structure of tree mortality (Moran's I). The regressions controls flexibly for weather and includes zip code and state-year fixed effects. Standard errors (in parentheses) are clustered two ways by state-year and zip code. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

While I do not find evidence the effect of tree mortality on ecosystem services depends on its spatial distribution, this analysis does not rule out other differences, such as how different causes of death affect the quality of wood or the integrity of the root structure. These differences are more difficult to investigate with existing data but merit further investigation. Thus the estimates provided here should be interpreted as the effect of tree mortality caused by bark beetles, and caution should be exercised when extrapolating these values to other types of tree mortality. Still, the effect of beetle-induced mortality is highly policy-relevant as bark beetles are the leading cause of tree mortality in the Western US, having damaged more than 58 million acres since 2000.

Valuing the social cost of tree mortality. To provide a sense of scale for the damages caused by tree mortality in the American West, I extend my results to estimate the social cost of tree mortality that has occurred over the last two decades. The social cost is computed by combining the estimated marginal effects with location-specific measures of annual tree mortality and the geographic distribution of people and capital (see SI Appendix D for additional details).

I find that between 1998 and 2018, tree mortality in American West decreased the value of timber tracts by \$1.1 billion; this amounts to 9.6% of total revenues from timber sales. Over the same period, I estimate that tree mortality decreased home values in the region by \$16.5 billion. In the most severely affected counties, including Larimer, Jackson, and Gilpin in Colorado, housing values declined 1.5% and 2% in response to widespread mortality ($>$ 10% of forest cover). It is noteworthy that the effect of tree mortality on non-market benefits, as measured by capitalization into home values, is an order of magnitude larger than the impact on the value of forest products that can be harvested and sold in the market, as measured by timber sales. Finally, I estimate that tree mortality increased damages from air pollution, wildfire, and flooding by \$233 million, \$676 million, and \$12 million, respectively, per year.

My estimates imply a social cost of approximately \$17.6 billion if we sum the damages to timberland and housing values alone. In theory, the hedonic estimates should capture the full amenity and environmental quality costs of tree mortality, so I elect not to include the economic costs of increased air pollution exposure, flood damages, or wildfire risk in this calculation. However, there are at least three reasons why my total social cost estimate should be interpreted as a lower bound. First, people most likely have incomplete information about levels of tree mortality and their welfare implications, suggesting that non-market values may not fully capitalize into property prices. Second, these numbers do not account for temporal or spatial spillovers in costs of tree mortality beyond the distances I include in my distributed lag models. For example, because the changes to carbon dynamics caused by tree mortality have welfare implications that are geographically disperse and may persist over decades, these costs are not fully captured by my approach. Third, my estimates do not account for non-use ("existence") values.

Figure 5 shows heterogeneity in the cost of tree mortality across counties. Notably, these estimates assume the same response functions across all counties, and spatial heterogeneity reflects differences in the level of tree mortality, geographic distribution of timberland, and value of the housing stock. As one might expect, reductions in the value of timberland versus housing are concentrated in different geographic areas. Rural, timber-producing regions such as Plumas County, CA experience the largest declines in timber tract revenues, while the costs to housing value are most pronounced in localities with a high density of homes (e.g. Southern California). Similar to

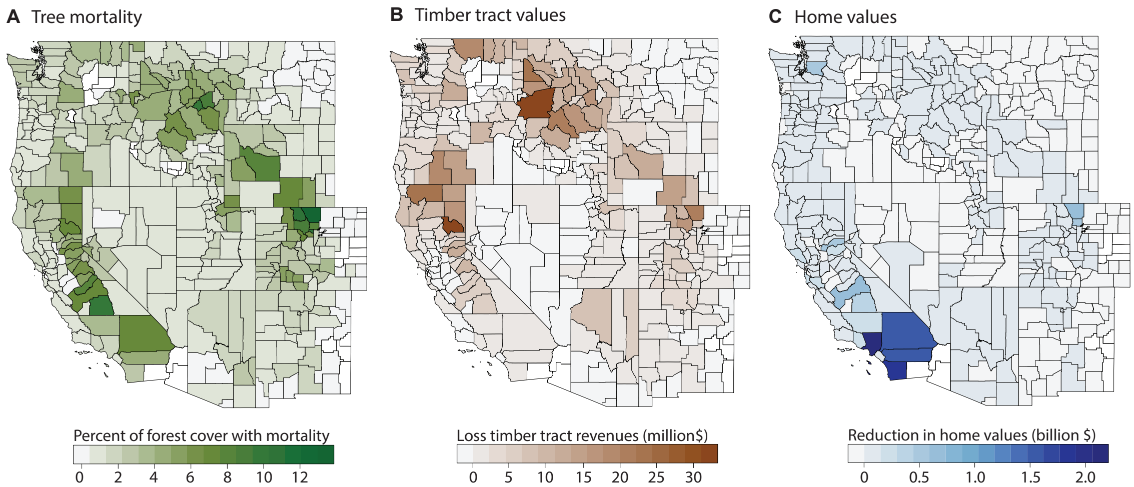

Figure 5: **The social cost of tree mortality in the American West**. See SI Appendix D for estimation details. (A) Average (across years) percent of forest cover with tree mortality by county. (B) Annual reductions timber tract revenues, reported in million dollars (C) Reductions in the value of the housing stock, reported in billion dollars.

the effect on housing values, the largest social costs from reduced capacity to provide regulating services such as air quality improvement and flood protection occur in areas where high levels of tree morality coincide with high population densities.

Conclusion

This paper exploits a natural experiment to assess the welfare consequences of changes in forest health. I demonstrate that the thermal threshold at which cold-induced mortality occurs in damage agents such as bark beetles can be used to isolate plausibly random changes in tree mortality. I then use this quasi-experimental setting to quantify the effect of tree morality on ecosystem services in the American West. I find that tree mortality has significant and economically meaningful impacts on both the market value of forests and the non-market amenity and environmental quality benefits these ecosystems provide. I estimate that over the last two decades, tree mortality has reduced the social value of forests by approximately $17.6 billion, with the majority of the damages coming from non-market benefits.

My results have important policy implications. Tree mortality rates are only expected to worsen in the coming decades as changing temperature and precipitation patterns lead to increased heat stress, drought, and movement of damage agents to higher latitudes and elevations (Allen et al., 2010; Bentz et al., 2010). Yet, federal funding for forest health issues has declined sharply in recent years (Gandhi et al., 2019). Management of forest die-off poses unique challenges given the rapid development, extensive spatial scale, and severity of recent tree mortality events (Seybold et al., 2018). Two broad approaches are used: long-term prevention techniques to increase stand resilience (silviculture) and suppression measures to control pest outbreaks or remove dead trees after the damage has already occurred. While silvicultural techniques are thought to be the most effective approach in the long-run, these expenses can be hard to justify when communities cannot yet see the costs of inaction (Samman and Logan, 2000). With costs in the range of $100 to $1,000 per acre, the expense of implementing silviculture practices throughout American forests would exceed current levels of public funding for investments in forest health (Donovan and Brown, 2005).

By quantifying the social cost of tree mortality, my findings can assist decision makers in trading off the costs and benefits of investments in forest health. To provide a simple heuristic for evaluating the cost effectiveness of such investments, I perform a back-of-the-envelope calculation to estimate a social cost for each dead tree. I estimate that the death of a tree in my sample costs society $43 in foregone benefits.[7] While this value and the other empirically-derived values reported in throughout the analysis are intended to inform policy, practitioners employing benefits transfer should exercise caution as my estimates represent the average social cost of beetle-caused tree mortality in the American West, but my results may not be representative of all regions or forest types. Indeed, as Figure 5 demonstrates, the cost of tree mortality is highly dependent on the local exposure of people and capital.

Methodologically, I contribute to the literature by demonstrating how plausibly exogenous variation in ecosystem health generated by a biological threshold can be used to generate quasi-experimental conditions. Conceptually similar approaches have been used to study the effects of

[7] This calculation is done by dividing my estimate of total social cost of tree mortality over the years 1998 to 2018 by the number of dead trees over the same period, as reported in the Insect and Disease Detection Survey annual reports.

insects on human health (Frank, 2017) and economic development (Alsan, 2015); however, to my knowledge, this is the first paper to exploit a such a threshold to identify causal effects in the context of ecosystem loss or degradation. Given that causal inference is particularly challenging in this literature and a number of biological thresholds are well established, this approach could be applied more broadly. For example, one might study the effect of changes in the health of coral reef ecosystems using the thermal threshold at which coral bleaching occurs.

I use a reduced-form statistical approach that captures the real-world response of ecosystem services to changes in forest health without requiring that I explicitly model the underlying mechanisms (e.g. I estimate the response of flood damages to tree mortality without modelling changes to the hydrological cycle). This methodology is particularly useful in the context of forest degradation, where the impact of tree mortality on many ecosystem functions remains uncertain (Anderegg et al., 2013). However, my results should be not viewed as a substitute for process-based models that characterize the causal pathways between tree mortality and ecosystem services. Instead, my findings are intended to complement these process-based models by, for example, helping to calibrate the values of key parameters.

I conclude by noting two additional limitations of my study. For one, I only examine a handful of the many benefits forests provide to society. In addition to the ecosystem services evaluated here, forests provide critical ecological functions such as carbon storage and sequestration, nutrient cycling, water purification, and wildlife habitat. While some of these benefits may capitalize into local property values, the full value of services with large off-site benefits are unlikely to be captured by my approach. Carbon storage and sequestration is a prominent example of such a service, and while this is perhaps the best studied regulating service provided by forests, most of our current understanding comes from process-based models rather than empirical evaluations (Fei et al., 2019). Relatedly, my findings offer new insight into the economic value of forests, but they provide an incomplete picture because I only observe the effects of forest die-off and not deforestation. Because regeneration can rapidly replace lost biomass, there are many reasons to believe the that forest die-off is far less damaging to ecosystem services than conversion of the land to another use. However, it is worth noting that deforestation generally contributes to human well-being in other ways, such as allowing for increased food production or economic development; whereas, society receives fewer direct benefits in return for forest degradation.

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Supplementary Information

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A Data Appendix

A.1 Variable definitions and construction

Variable	Description	Construction
Tree mortality (M)	Percent of forested area in which tree morality has been detected.	$M = \frac{\text{Acres with tree mortality}}{\text{Acres of forest cover}}$
Beetle prevalence (D)	Percent of basal area on which bark beetles have been detected.	$D = \frac{\text{Basal area with beetle damage}}{\text{Total basal area}}$
Winter survival (WSI)	Prediction of the proportion of bark beetles to survive the winter.	Constructed using a cold tolerance model developed by Régnière and Bentz (2007). See *Methods*.
Beetle exposure (B)	Proportion of beetles to survive the winter, scaled by a location-specific proxy mesure for bark beetle prevalence.	$B = WSI \times D$
Temperature controls ($\boldsymbol{T}$)	Vector of daily temperature bins. These variables count of the number of days with mean temperatures in 2°C intervals (e.g. number of days with a mean temperature in the range 0°C to 2°C).	$\boldsymbol{T} = (T_1, T_2, ...T_{31})$ where there are 31 bins, T_k, ranging from -30°C to 30°C in 2°C intervals. $T_k = \sum_d t_d$ where $t_d = 1$ if the mean temperature on day d was in interval k and $t_d = 0$ otherwise.
Precipitation controls ($\boldsymbol{P}$)	Vector of second-order polynomials in monthly precipitation.	$\boldsymbol{P} = (P_1, P_2, ...P_{12})$ where P_m, is a second-order polynomial in total precipitation for month m.
Zip code fixed effects (α_i)	Capture unobserved time-invariant factors in each location.	Dummy variable for each zip code.
State-year fixed effects (δ_{st})	Capture common nonlinear trends and year-specific common shocks within each state.	State by year dummy variables.
Ecosystem services ($Outcome$)	One of five social or economic outcomes quantifying the benefits humans derive from forests.	*Outcome* is equal to the price per acre of timberland, log mean home value, log PM2.5 concentrations, log flood damages, or log wildfire burned area.

Table A1: **Variable descriptions and construction.** This table describes the variables used in this analysis and how they are constructed from the raw data. Details on each data source are provided in the Data Appendix that follows.

A.2 Summary Statistics

	Mean	St.Dev.	Min.	Max.	N
Forest health data					
Area affected by tree mortality (acres)	1,438	7,527	0	363,530	59,736
Forested area (acres)	69,683	114,191	44	1,752,152	59,736
Percent of forest with tree mortality (%)	1.11	3.36	0.00	24.89	59,736
Basal area with bark beetles (square feet per acre)	123	353	0	7,836	59,736
Total basal area (square feet per acre)	1,166	2,331	0.02	47,741	59,736
Bark beetle prevalence (%)	4.11	4.64	0.00	27.15	59,736
Indicator for bark beetles	0.62	0.48	0.00	1.00	59,736
Ecosystem service outcomes					
Timberland value (price per acre)	6,619	11,230	0.025	623,448	17,667
Harvest volume (thousand board feet)	2,604	2,812	1	31,215	17,667
Mean home value ($)	223,084	199,350	16,553	3,361,,445	28,831
Ambient PM2.5 concentrations (μg/m^3)	5.47	2.21	0.70	26.85	59,736
Flood insurance claims ($)	7,732	192,478	0	20,168,074	59,736
Wildfire burned area (acres)	366	3,105	0	240,960	59,736
Climate controls					
Days with temperature < -30°C	0.00	0.06	0.00	3.71	59,736
Days with temperature -30°C to -28°C	0.01	0.12	0.00	4.71	59,736
Days with temperature -28°C to -26°C	0.03	0.20	0.00	6.00	59,736
Days with temperature -26°C to -24°C	0.05	0.30	0.00	9.00	59,736
Days with temperature -24°C to -22°C	0.10	0.42	0.00	7.97	59,736
Days with temperature -22°C to -20°C	0.16	0.58	0.00	12.00	59,736
Days with temperature -20°C to -18°C	0.27	0.82	0.00	15.52	59,736
Days with temperature -18°C to -16°C	0.45	1.10	0.00	16.00	59,736
Days with temperature -16°C to -14°C	0.76	1.56	0.00	17.00	59,736
Days with temperature -14°C to -12°C	1.28	2.32	0.00	20.65	59,736
Days with temperature -12°C to -10°C	2.16	3.44	0.00	28.00	59,736
Days with temperature -10°C to -8°C	3.57	5.02	0.00	32.00	59,736
Days with temperature -8°C to -6°C	5.61	6.90	0.00	38.85	59,736
Days with temperature -6°C to -4°C	8.36	8.94	0.00	48.15	59,736
Days with temperature -4°C to -2°C	11.69	10.95	0.00	53.51	59,736
Days with temperature -2°C to 0°C	15.52	12.58	0.00	62.00	59,736
Days with temperature 0°C to 2°C	19.54	13.11	0.00	64.58	59,736
Days with temperature 2°C to 4°C	23.36	12.47	0.00	69.00	59,736
Days with temperature 4°C to 6°C	26.72	12.29	0.00	76.13	59,736
Days with temperature 6°C to 8°C	28.82	12.29	0.00	83.00	59,736
Days with temperature 8°C to 10°C	29.50	11.80	0.00	101.00	59,736
Days with temperature 10°C to 12°C	29.09	11.47	3.00	117.00	59,736
Days with temperature 12°C to 14°C	28.67	12.59	6.83	142.00	59,736
Days with temperature 14°C to 16°C	28.12	12.41	1.59	137.06	59,736
Days with temperature 16°C to 18°C	26.93	11.06	0.00	112.00	59,736
Days with temperature 18°C to 20°C	24.12	10.98	0.00	108.00	59,736
Days with temperature 20°C to 22°C	19.67	11.71	0.00	94.00	59,736
Days with temperature 22°C to 24°C	14.44	12.19	0.00	73.00	59,736
Days with temperature 24°C to 26°C	8.97	10.92	0.00	66.59	59,736
Days with temperature 26°C to 28°C	4.53	7.84	0.00	59.69	59,736
Days with temperature 28°C to 30°C	1.79	4.48	0.00	60.00	59,736
Days with temperature $>$ 30°C	0.72	4.16	0.00	138.00	59,736
Precipitation, January (mm)	93.97	111.25	0.00	1105.97	59,736
Precipitation, February (mm)	82.35	95.97	0.00	1029.14	59,736
Precipitation, March (mm)	82.19	89.87	0.00	1050.68	59,736
Precipitation, April (mm)	59.67	52.49	0.00	517.51	59,736
Precipitation, May (mm)	49.97	45.40	0.00	378.93	59,736
Precipitation, June (mm)	34.06	35.96	0.00	409.98	59,736
Precipitation, July (mm)	27.25	32.43	0.00	373.40	59,736
Precipitation, August (mm)	29.58	33.45	0.00	355.19	59,736
Precipitation, September (mm)	33.23	37.21	0.00	426.14	59,736
Precipitation, October (mm)	57.00	61.53	0.00	723.52	59,736
Precipitation, November (mm)	82.34	104.61	0.00	1368.46	59,736
Precipitation, December (mm)	107.81	128.45	0.00	1660.68	59,736

Table A2: **Summary statistics.** Observations at the zip code by year level for all zip codes in the Western US. Data on forest health are from the US Forest Service and climate controls are from the Climate PRISM Group. See SI Appendix C.4 for details on ecosystem service outcomes.

A.3 Forest health data

I obtain data on annual tree mortality from the Insect and Disease Survey (IDS). The IDS is a collection of geospatial data that maps the extent of damage from insects, disease, and other types of forest disturbances. The data is collected by the USFS's Forest Health Protection (FHP) unit and partners in State agencies using low-altitude aerial surveys and ground surveys. Trained observers visually scan 5km-wide swaths of forest as they fly along a grid pattern. Using digital mobile sketch mapping (DMSM) tablets, areas with damaged trees are recorded as spatial polygons. I use these mortality polygons, in combination with spatial information on the extent of forest cover from the National Land Cover Database (NLCD), to construct the primary measure of tree mortality used in this analysis: the percent of forest cover with tree mortality. Alternatively, one could measure tree mortality in absolute area (acres). I show the robustness of my main results to this alternative measure in SI Appendix B.4.

The core benefit of the IDS data is that it provides annual observations covering nearly all forested areas in the Western US. There are two important limitations to this data. First, all measurements are approximate "footprint" areas, which delineate areas of visible damage. Unaffected trees may exist within the mortality polygons, and the amount of damage within the footprint is not reported prior to the year 2014. That is, tree mortality is measured in acres of forested area in which damage has been detected rather than a more precise measure such as basal area loss. Second, because the data collectors differ across locations and years, there is substantial variation in how areas of damage are recorded. For example, one operator may outline one polygon encompassing a large area with tree mortality, while another operator may delineate the same area using many smaller polygons around the precise locations in which the mortality is concentrated. Section B.3 discusses the robustness of my estimation approach to these two sources of measurement error.

I complement the tree mortality data with spatial information on the biological range bark beetles from the Forest Inventory and Analysis (FIA) unit's National Forest Damage Agent Range Map (USFS, 2019b). The FIA uses ground surveys to estimate the amount of "basal area" (area of land occupied by tree trunks) with damage attributable to bark beetles. Bark beetle damage is usually easy to identify for trained surveyors as beetles leave unique signatures, including characteristic fading patterns of the tree crowns (Figure A1A), pitch tubes or brown boring dust on the outside of the bark, and galleries beneath the bark (Figure A1B). Although the Damage Agent Range Map is only available in the cross-section for the year 2012, it allows me to construct a proxy measure for bark beetle prevalence in each location (Figure A1C). I define bark beetle prevalence as the percent of total basal area on which bark beetles have been detected. Across location, the mean level of bark beetle prevalence is 6.6%.

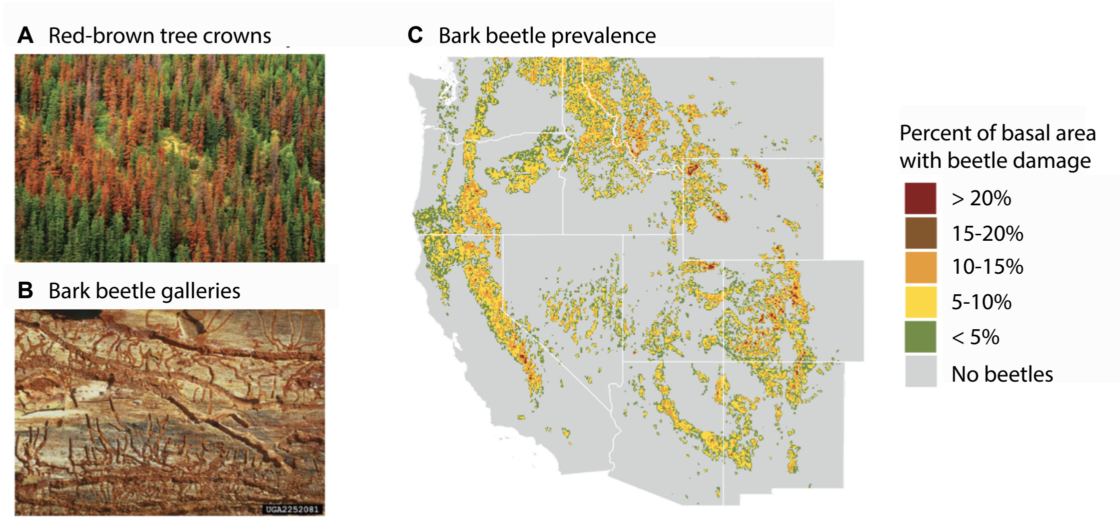

Figure A1: **Data on bark beetle prevalence from the National Damage Agent Range Map.** Estimates of total basal area loss attributable to bark beetles were collected in 2012 by the Forest Inventory and Analysis (FIA) unit using ground surveys. Surveyors are trained to recognize the signatures of bark beetles, including red-brown tree crowns (A) and characteristic galleries beneath the bark (B). I define bark beetle prevalence as the percent of total basal area with damage from bark beetles (C).

A.4 Ecosystem service outcomes

Ecosystem services provided by forests can be separated into two broad classes: goods and services that are priced in the market (e.g. timber) and non-market benefits (e.g. air quality improvement) for which assigning economic value is more challenging. I measure the provisioning value of forests using the per acre sales price of timber tracts on public land. This price captures the value of forest products that can be harvested and sold in the market. I measure non-market benefits using the hedonic pricing method, which quantifies willingness to pay for the amenity and environmental quality benefits of healthy trees (see SI Appendix B.1 for details on the hedonic method).

Timberland value. I obtain transition-level records of sales conducted by the USFS, the Bureau of Land Management (BLM), and state agencies from the Timber Data Company. These data contain information on the date, location, and sales price, as well as detailed attributes of the timber tract such as harvest acres, harvest volume, and estimated logging costs.

Home values. I examine capitalization of tree mortality into home values using data on the prices of single-family residences from Zillow Research. Specifically, I use the zip code-level Zillow Home Value Index (ZHVI) Single-Family Home Time Series data product, which measures typical home values within a zip code. The ZHVI is constructed from Zestimates, which Zillow regularly calculates for more than 100 million individual homes nationwide. Zestimates incorporate data from a variety of sources including public records, user-submitted data, and real estate data from direct feeds or multiple listing services. More information on the ZHVI methodology is available from Zillow Research at https://www.zillow.com/research/zhvi-methodology-2019-deep-26226/.

Air quality. I measure air quality using annual concentrations (in micrograms per cubic meter) of ground-level fine particulate matter (PM2.5), with dust and sea-salt removed, from the the Global Annual PM2.5 Grids from MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD) with GWR (van Donkelaar et al., 2018). This data product is constructed by relating satellite-derived measures of AOD to near-surface PM2.5 concentrations using the GEOS-Chem chemical transport model. Specifically, Geographically Weighted Regression (GWR) is used in combination with ground-level measurements of PM2.5 to predict PM2.5 concentrations on a 0.01 degrees resolution grid.

Flood damages. Data on flood damages come from the National Flood Insurance Program (NFIP) Redacted Policies Dataset (Dombrowski et al., 2019). This dataset comprises the NFIP's full claim history and represents more than 2 million transactions. I construct the dependent variable as sum of claims payments for property damage to buildings and their contents.

Wildfire burned area. I obtain data on the spatial extent of wildfires from the Monitoring Trends in Burn Severity (MTBS) program (Eidenshink et al., 2007). The MTBS is an interagency program conducted by the U.S. Geological Survey Center for Earth Resources Observation and Science and the USDA Forest Service Geospatial Technology and Applications Center. The program maps the burn severity and extent of large fires across the entire United States from 1984 to present. The data set includes all fires with areas of 1,000 acres or greater in the western US.

A.5 Climate data

My estimation strategy requires high spatial and temporal resolution climate data to construct the WSI and to capture non-linear relationships between climate, tree mortality, and ecosystem services. I use daily temperature and monthly precipitation data from the PRISM Climate Group, which provides gridded observations at 4km resolution. The PRISM Climate Group collects observations from a wide range of weather monitoring networks, applies quality control measures, and then implements the PRISM (Parameter-elevation Relationships on Independent Slopes Model) interpolation method to construct gridded datasets. The interpolation is done by calculating a climate–elevation regression for each grid cell, where stations entering the regression are assigned weights based primarily on the physiographic similarity of the station to the grid cell (Daly et al., 2008).

In order to match the climate data with the information on tree mortality and ecosystem services, I convert these measures to annual observations and aggregate them to the zip code level. To preserve inter-annual variability in temperature, I bin mean daily temperature into 2°C intervals, such that for each location and year I have a count of the number of days with temperatures in the range of 0°C to 2°C, 2°C to 4°C, 4°C to 6°C, and so on. I account for precipitation using second-order polynomials in monthly precipitation as to allow for differential response to precipitation over the course of the year. Because there are multiple grid cells per zip code, I aggregate grid-level temperature and precipitation values to zip code-level observations weighing by treed area.

B Estimation methods

B.1 The hedonic pricing method

The hedonic pricing method is commonly used to estimate the economic value of non-market environmental goods and services. It is based on the insight that a consumer's valuation of a differentiated product, such as housing, is determined by the how much the consumer values its individual characteristics. We can describe a house as a vector of its individual characteristics, $Q = (q_1, q_2, \ldots, q_n)$, including features of the home (e.g. number of bedrooms), neighborhood amenities (e.g. local schools), and environmental quality (e.g. air quality). The price of the house can therefore be written as a function of its characteristics, $P(q_1, q_2, \ldots, q_n)$. The partial derivative of the price function with respect to the n^{th} characteristic, $\partial P/\partial q_n$, is the marginal price of the n^{th} characteristic implicit in the overall price of the house. This value represents the change in the price of the home due to a marginal increase in the n^{th} characteristic, holding all else constant.

Assuming that the housing market is competitive, equilibrium home prices are determined by the interactions between buyers' demand for housing and sellers' supply of housing. The marginal implicit price of a disamenity, such as tree mortality, gives the equilibrium differential that allocates buyers across locations and compensates those who face higher levels of the disamenity. All else equal, locations with higher levels of the disamenity must have lower housing prices to attract buyers. Thus we can interpret the marginal implicit price of the disamenity as the consumer's marginal willingness to pay (MWTP) to for the disamenity, where a negative price indicates willingness to pay to avoid the disamenity.

B.2 Instrumental variables and two stage least squares (2SLS)

Causal inference in the ecosystem services literature is challenging because it is rarely possible to manipulate ecosystems at scale. In the absence of random assignment, studies linking changes in ecosystem health to changes in ecosystem services may only measure the magnitude of the association, rather than the magnitude and direction of causation which is needed for decision making. To overcome this challenge, this study uses an instrumental variables (IV) approach to generate quasi-experimental conditions.

The goal of IV methods is to isolate a subset of the variation in the treatment that is as good as randomly assigned. This is done by finding an "instrument" that is correlated with the treatment, but that is otherwise independent of the outcome. That is, the instrument must only affect the outcome through the treatment. I use days with temperatures below the supercooling point (SCP) of bark beetles as an instrument for tree mortality. I show that in years with more days below the SCP, fewer bark beetles survive the winter, resulting in significantly lower levels of tree mortality that summer. Intuitively, this natural experiment allows me to compare a forest to itself in two years with similar temperature and rainfall distributions, but in one year the forest is "treated" with one additional day below the SCP and thus experiences less tree mortality. I implement this approach using the two stage least squares (2SLS) estimator.

First-stage. The first stage estimates the relationship between the treatment and the instrument. I estimate the impact of bark beetles on tree mortality, modeling the percent of forest cover with tree mortality, M, as a linear function of bark beetle exposure, B. Bark beetle exposure is modeled as the interaction between the winter survival instrument (WSI) and bark beetle prevalence (the proportion of basal area on which bark beetles have been detected). The first-stage equation from the main text can be simplified to

$$M_{ist} = \pi B_{ist} + \theta \boldsymbol{X}_{ist} + \mu_{ist} \tag{8}$$

where $\boldsymbol{X}_{ist}$ is a vector of covariates including controls for weather, zip code fixed effects, and state-year fixed effects. In the 2SLS system, the first stage allows me to generate plausibly exogenous changes in tree mortality caused by the discontinuity in bark beetle survival at the SCP. Mechanically, this is done by taking the predicted values of tree mortality from this regression, $\hat{M}_{ist}$, and using them in place of the actual values of M_{ist} in the second stage.

Second-stage. The second stage estimates the relationship of interest, the effect of tree mortality on ecosystem services. The second-stage equation is

$$Outcome_{ist} = \beta \hat{M}_{ist} + \theta \boldsymbol{X}_{ist} + \epsilon_{ist} \tag{9}$$

where $Outcome_{ist}$ is one of the ecosystem service outcomes and all other variables are defined as above.

Reduced-form. The 2SLS system also allows for the reduced-form estimation of the relationship between the instrument and the outcome variable. That is, it estimates of the effect on bark beetle exposure on ecosystem service outcomes. The reduced-form equation is

$$Outcome_{ist} = \gamma B_{ist} + \theta \boldsymbol{X}_{ist} + \nu_{ist} \tag{10}$$

If the identifying assumption holds, then bark beetle exposure is exogenous conditional on the covariates, so the estimate of γ can be interpreted as a causal effect. However, note that this effect should run only through tree mortality.

Identifying assumptions. My IV approach requires two main assumptions: (1) the WSI causes variation in tree mortality and (2) the WSI does not have a direct effect on the ecosystem services (i.e. the WSI only affects ecosystem services indirectly through tree mortality). The first assumption can be directly tested using the first-stage equation. The second assumption cannot be directly tested; however, I provide evidence that the WSI is not simply picking up generic patterns between climate and ecosystem services by conducting a placebo test that shows a null effect of the WSI in forested areas without bark beetles.

B.3 First stage results

	Dependent variable: Tree mortality		
	Full sample	Property sample	Timber sample
	(1)	(2)	(3)
Bark beetle exposure	0.234***	0.240***	0.224***
	(0.020)	(0.029)	(0.035)
Observations	37,240	17,953	9,817
R^2	0.523	0.584	0.551
F-statistic	130.9	69.6	83.4

Table A3: **Effect of the instrument on tree mortality.** The dependent variable is the percent of forest affected by tree mortality. Bark beetle exposure is modeled as the interaction between predicted winter survival and baseline bark beetle prevalence (percent of basal area with damage from beetles). Standard errors (in parentheses) are clustered by zip code and by state-year. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

B.4 Robustness to measurement error in the tree mortality data

As discussed in SI Appendix A.3, there are two notable sources of measurement error in the tree mortality data. First, all measurements are approximate "footprint" areas, which delineate areas of visible damage and may also include live trees. Assuming this type of measurement error is classical, it can lead to attenuation bias in the estimated effects (i.e. bias the effect of tree mortality on ecosystem services towards zero). However, any instrument that is correlated with tree mortality but uncorrelated with the level of measurement error will identify consistent parameter estimates. Thus the use of the winter survival instrument alleviates concerns about imprecise measures of tree mortality.

Second, because data collectors differ across locations and years, there is considerable variation in how areas of damage are recorded across surveys. We might be concerned that these systematic differences in how surveys are conducted are correlated with either the treatment (tree mortality) or outcome (ecosystem service). However, note that the inclusion of zip code and state-year fixed effects in the regression equations ensure that my estimates are robust to systematic differences in reporting across locations, which light arise from differences in how data collectors are trained by different Forest Service offices, as well as state-level changes in survey procedures over time, which might arise due to differences in funding across years.

B.5 Residual analysis

Estimation via ordinary least squares (OLS) requires the assumption that the values of the outcome variable are normally distributed around each value of the treatment. We can check this assumptions using residual plots, which display the value of the regression residuals as a function of the fitted values. My model log-transforms four dependent variables — home values, particulate matter, flood damages, and wildfire area — such that tree mortality has a multiplicative effect on these ecosystem service outcomes. Figure A2 displays the residual plots for the linear model (left) and log-transformed model (center). The log-transformed models appear to better satisfy the random error assumptions OLS. The right column of Figure A2 plots the distribution of residuals for the log-transformed model. Reassuringly, these residuals very closely approximate a normal distribution.

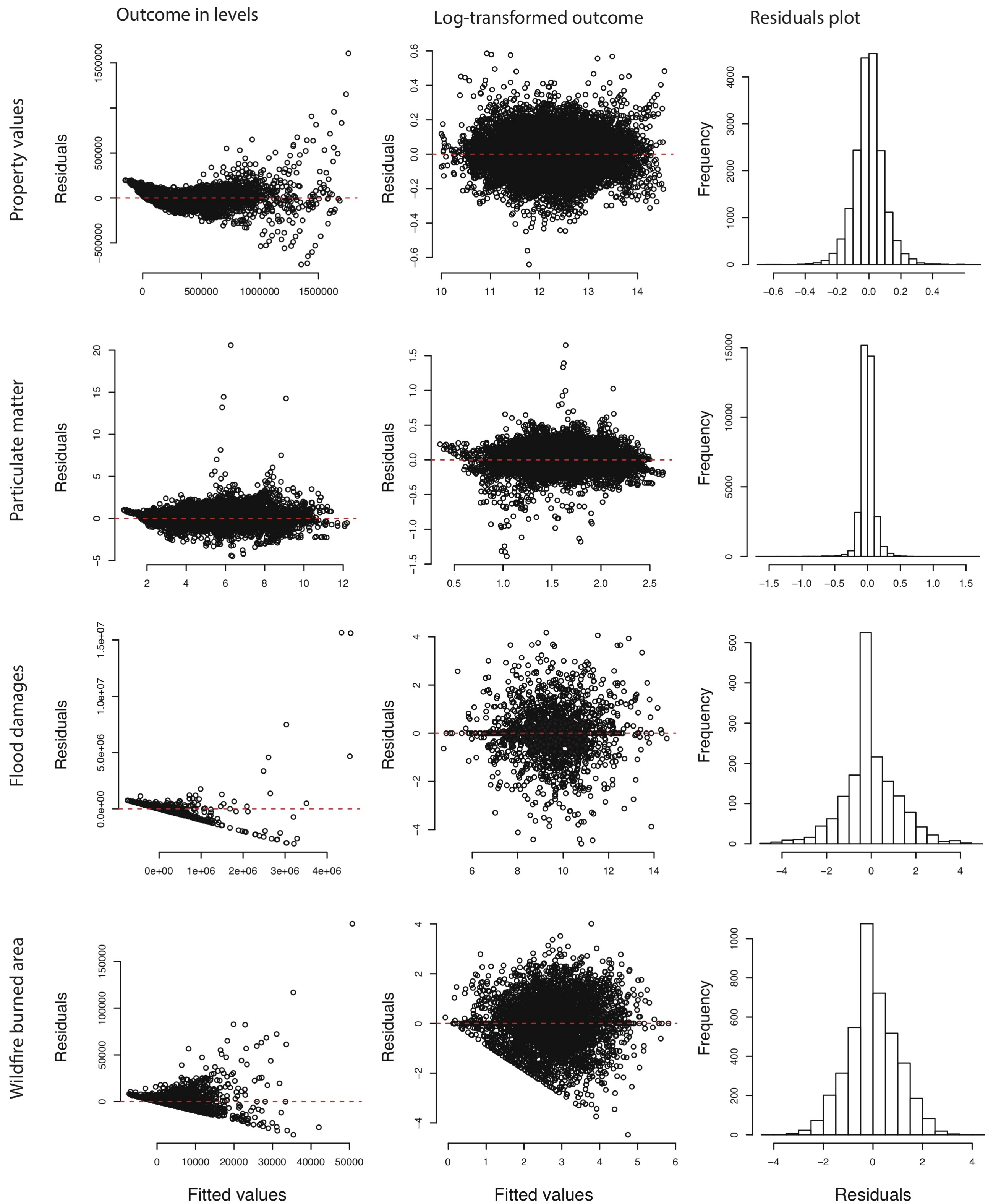

Figure A2: **Residual analysis.** The left and center columns plot the regression residuals as a function of the fitted values for the models where the dependent variable is specified in levels and logs, respectively. The right column plots the distribution of the regression residuals for the model where the outcome is log-transformed, which is the specification used in the main analysis.

C Robustness of the main results

C.1 An alternative measure of tree mortality

	Dependent variable:					
	Timber tract value	Timber tract volume	Log mean home values	Log PM2.5	Log flood damages	Log wildfire burned area
	(1)	(2)	(3)	(4)	(5)	(6)
Tree mortality acres	−144.6***	−222.72***	−0.0012***	0.0007*	0.0056***	0.0020
	(68.9)	(456.1)	(0.0003)	(0.0004)	(0.0015)	(0.0014)
Observations	17,953	17,953	17,953	37,240	37,240	37,240

Table A4: **Robustness to an alternative definition of tree mortality**. I re-run Equation 4 but this time define the tree mortality treatment variable as the absolute area affected by tree mortality (measured in thousand hectares) rather than as the percent of forest cover affected by tree mortality. All regressions control flexibly for weather and includes zip code and state-year fixed effects. Standard errors clustered at the state level are reported in parentheses. Asterisks indicate statistical significance at the 10% (*), 5% (**), and 1% (***) levels.

C.2 Alternative functional form assumptions

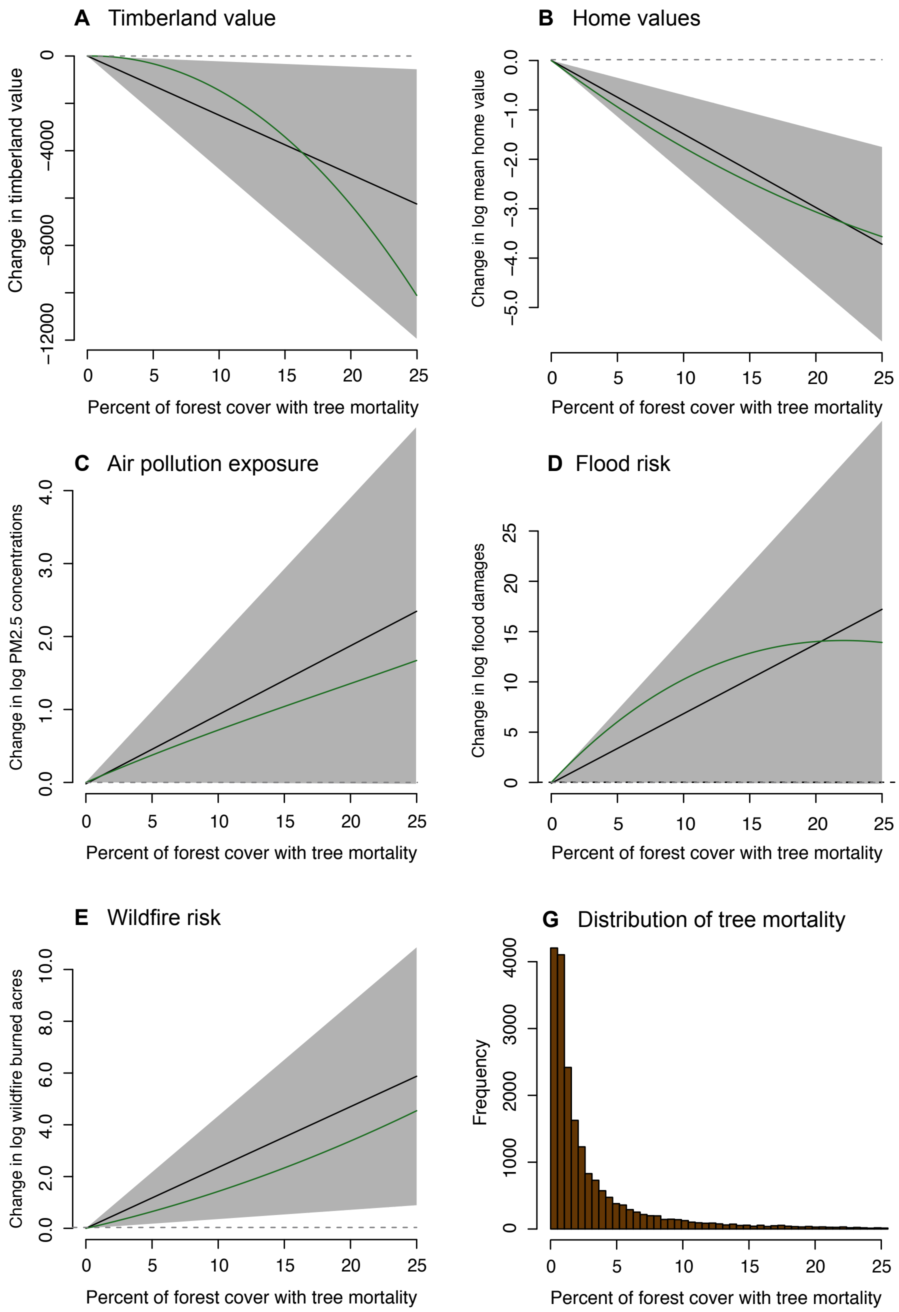

Figure A3: **Non-linear response of ecosystem services to tree mortality.** I re-estimate Equation 4 specifying the effect of tree mortality on ecosystem services using a third-order polynomial rather than restricting the response to be linear. This figure plots ecosystem service outcomes a function of tree mortality using both approaches. As in Table 1, coefficient estimates are multiplied by 100 for demonstration purposes for Panels B-E. Note that the x-axis ends at 25% as this is the maximum level of tree mortality I observe in the data.

C.3 Sensitivity to withholding regional blocks of data

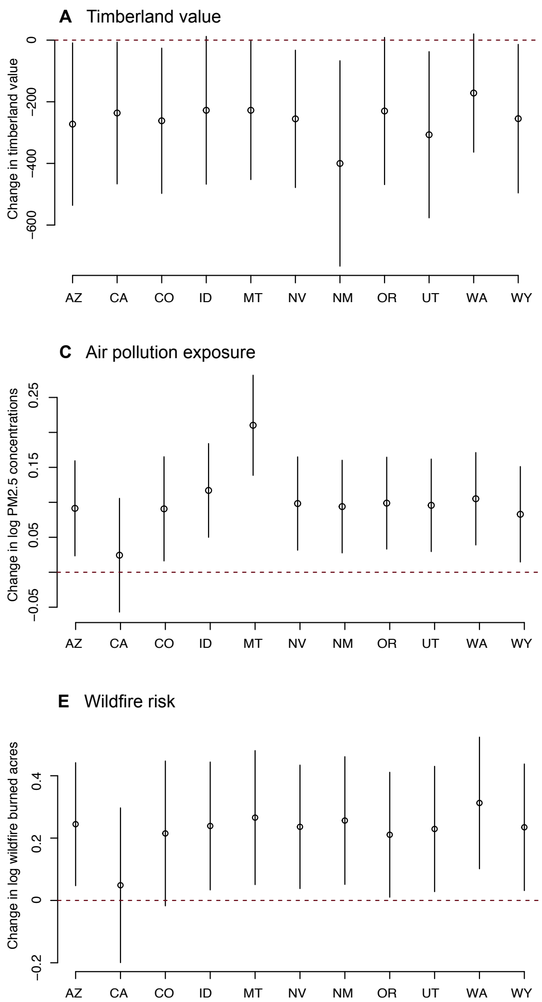

Figure A4: **Leave-one-out sensitivity analysis.** This test re-runs Equation 4 eleven times, each time dropping one state from the sample. The omitted state is indicated on the x-axis. Circles show coefficient estimates and whiskers show 95% confidence intervals. As in Table 1, coefficient estimates are multiplied by 100 for demonstration purposes in Panels B-E.

C.4 Is there evidence of rapid regrowth after tree mortality?

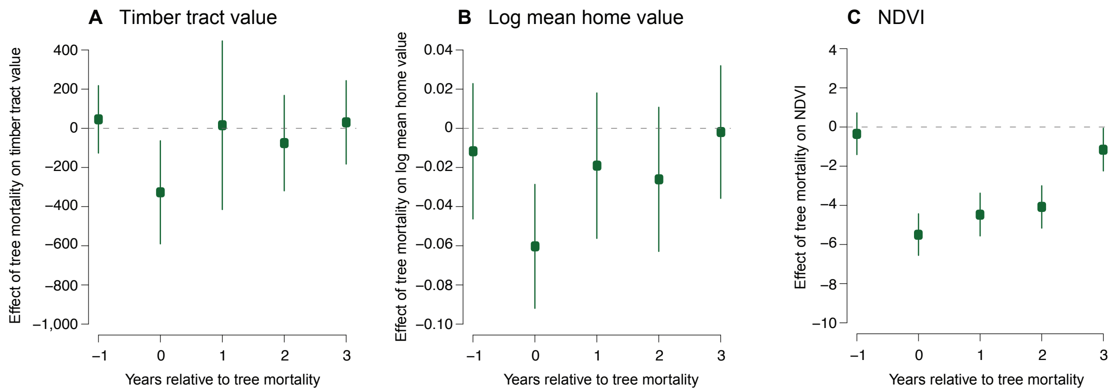

Figure A5: **Transient response of ecosystem services and green vegetation to tree mortality.** (A) and (B) are repeated from Figure 4 and show the effect of temporal lags of tree mortality on timber tract values (measured in price per acre) and log mean home values, respectively. (C) Shows the effect of temporal lags of tree mortality on the Normalized Difference Vegetation Index (NDVI), a simple indicator of live green vegetation.

C.5 Comparison of forests with and without bark beetles

	Forests with beetles (1)	**Forests without beetles** (2)	**Difference of means** (3)	**p-value from t-test** (4)
Forest health data				
Area affected by tree mortality (acres)	1,531	1,365	166	0.01
Forested area (acres)	94,001	50,435	43,566	0.00
Percent of forest with tree mortality (%)	1.17	1.07	0.10	0.00
Basal area with bark beetles (square feet per acre)	197.5	0	197.5	0.00
Total basal area (square feet per acre)	2,988	2,369	619	0.00
Bark beetle prevalence (%)	6.61	0.000	6.61	0.00
Indicator for bark beetles	1.00	0.00	1.00	0.00
Ecosystem service outcomes				
Timberland value (price per acre)	6,083	7,290	−1,207	0.23
Harvest volume (thousand board feet)	3,029	2,663	366	0.31
Mean home values ($)	222,168	224,002	−1,834	0.43
Ambient PM2.5 concentrations (μg/m^3) 2.50	5.47	5.48	−0.01	0.72
Flood insurance claims ($)	6,995	8,468	−1,474	0.35
Wildfire burned area (acres)	398	331	67	0.01
Observations	37240	22496		

Table A5: **Comparison of forests with and without bark beetles.** Columns (1) and (2) show mean values of forest health measures and ecosystem service outcomes in forests with and without bark beetles, respectively. Column (3) shows the difference in means and (4) reports the p-value from a Welch Two Sample t-test with the null hypothesis that the difference in means is equal to zero.

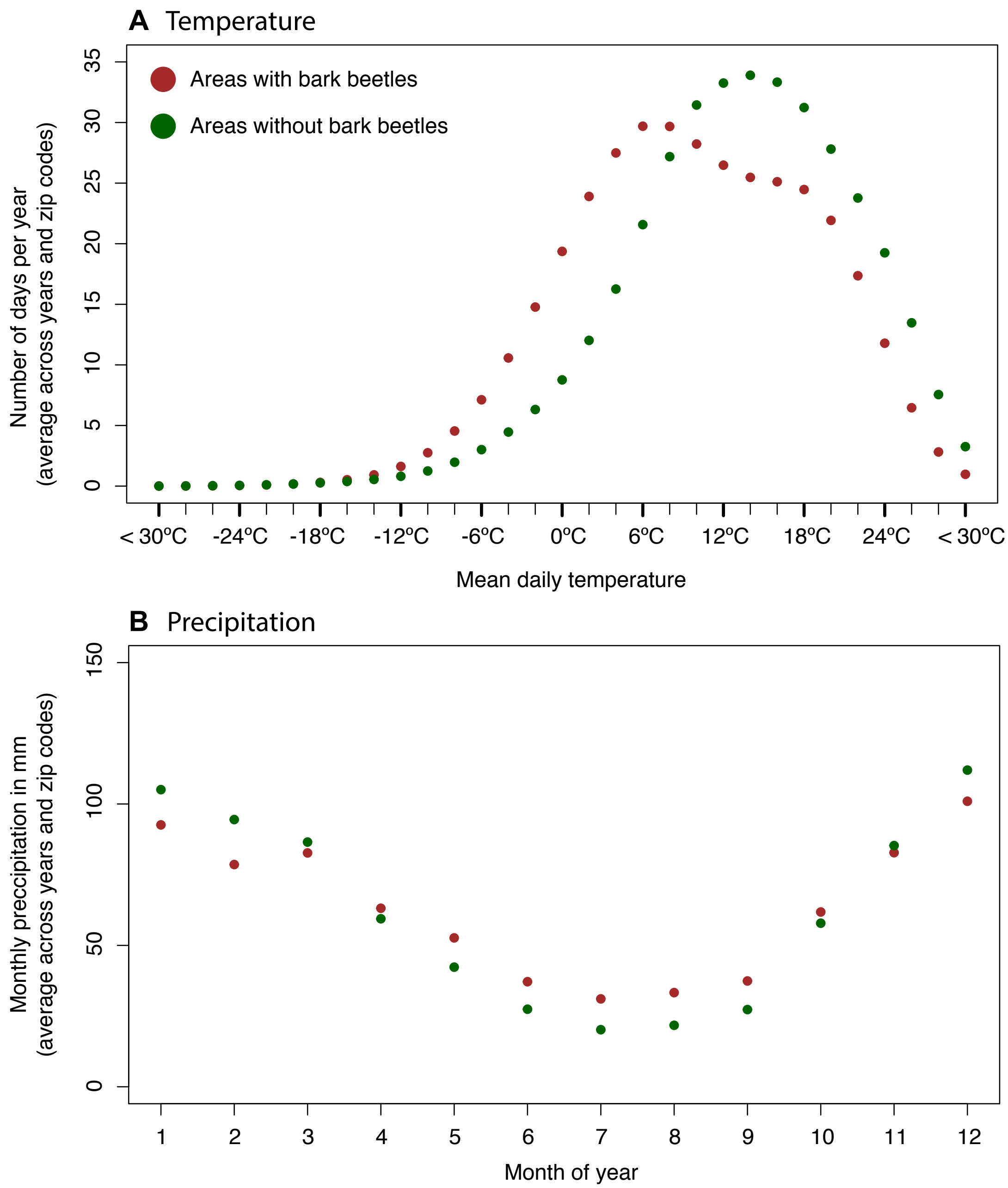

Figure A6: **Comparison of climate in forests with and without bark beetles.** (A) shows the distribution of daily temperatures, in 2°C intervals, in the mean zip code with bark beetles (green) as compared to the mean zip code without the pest (brown). (B) Same but for monthly precipitation.

D Valuating the social cost of tree mortality

To provide a sense of scale for the damages caused by tree mortality in the American West, I extend my results to calculate the social cost of tree mortality that occurred over the sample period, from 1998 to 2018. I compute the social cost for each county in the Western US by multiplying the estimated marginal effects by county-level annual tree mortality times location-specific measures of the amount of people or capital affected. I use the following sources of data:

Timberland acreage: I obtain county-level data on the acreage of timberland sold each year from the US Department of Agriculture's Timber Product Output (TPO) reports.

Home values. I compute the value of the housing stock in each county by multiplying mean home values from Zillow Research by housing counts from the 2010 census.

Air pollution exposure. I calculate damages from air pollution exposure using estimates of the mortality cost of marginal increases in ambient PM 2.5 concentrations from Deryugina et al. (2019). These authors estimate that cost of a 1 μg/m3 increase is \$299,000 per million Medicare beneficiaries. I obtain annual county-level data on the number of Medicare beneficiaries from the Center for Medicare and Medicaid Service's Medicare Enrollment Dashboard.

Flood damages. I calculate annual, county-level flood damages from the National Flood Insurance Program's Redacted Claims Dataset. This data provides a lower bound for flood damages as less than 20% of the nation's homes are covered under the program.

Wildfire damages. I calculate annual, county-level wildfire burned acres from spatial data produced by the Monitoring Trends in Burn Severity Program. I assume that each acre of burned area causes economic damages of \$1,500 as estimated by Mercer et al. (2000).