Supplementary Appendix to

"The intersection between climate adaptation, mitigation, and natural resources: An empirical analysis of forest management"

List of contents

Appendix A. Share of artificial regenerated private/state owned forestland

Breakdown by species type

	Douglas-fir	Fir	Hemlock	Ponderosa	Other softwood	hardwood
Oregon	63%	9%	26%	15%	3%	4%
Washington	52%	16%	21%	6%	4%	6%

Note: We excluded California as the majority of forestland are naturally regenerated, except for ponderosa pine, of which about 30% is artificially regenerated.

Breakdown by state

	Share of artificial regeneration
California	6%
Oregon	38%
Washington	33%
Entire region	25%

Appendix B. Monte Carlo simulation

Following the framework developed by Lewis and Plantinga (2007), the estimated probabilities are used in a Monte Carlo analysis to generate repeated realizations of the time-path of landscape change. To illustrate how the simulation uses the estimated forest management probabilities to generate landscape outcomes, consider the estimated probabilities of "clear-cut", "partial-cut", or "no-cut" in the harvest nest. We first draw a random vector of estimated parameters for the full model (Krinsky and Robb 1986)[1] and then calculate all management and natural disturbance probabilities. Since the harvest probabilities necessarily sum to one, we next draw a uniform random number r_1 between zero and one and compare it to the clear-cut probability. A clear-cut occurs if r_1 is less than or equal to the estimated clear-cut probability for that plot; a partial-cut occurs if r_1 is above the clear-cut probability but less than or equal to the sum of the clear-cut and partial-cut probabilities; a no-cut management action occurs otherwise. As in Lewis (2010), the simulation procedure accounts for the variation in the estimated parameters and random error terms by using random draws for the estimated parameters and for determining the outcome. We use all estimated probabilities of management and natural disturbance in a similar fashion.

[1] A simulated parameter vector is equal to $\beta_s = \hat{\beta} + C'X_K$, where $\hat{\beta}$ is the estimated parameter vector, C is the KxK Cholesky decomposition of the estimated variance-covariance matrix, and X_K is a K-dimensional vector of draws from a standard normal distribution.

Appendix C. Calculation of rents

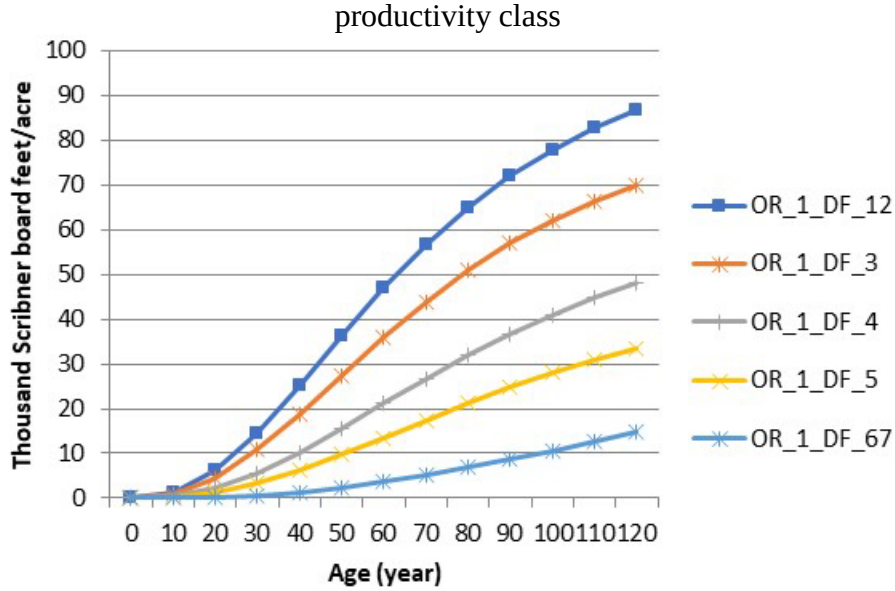
C.1. Calculation of timber rents

The rent for planting bare land, $\overline{rent}_{r(n)s_j t}$, which is specific to the planted tree species s_j in the region that contains plot *n* in time, measures annualized land value in equation (5). Rent is used in the econometric estimation of replanting decisions to approximate the economic value of planting the land in particular tree species. The rent calculation works as follows. Using the FIA plot-level data of stand volume and age, we estimate the coefficients α and β that fit the data to a von Bertalanfy (1938) growth equation:

$$\overline{\mathrm{vol}}_{r,s_i,sc}(\mathrm{AGE}, c_t) = \alpha_{r,s_i,sc}(1 - \exp(-\beta_{r,s_i,sc} * \mathrm{AGE}))\text{^}3 \qquad \text{(C.1)}$$

This is done for each site productivity class, species type, and price region. So, $\alpha_{r,s_i,sc}$ and $\beta_{r,s_i,sc}$ are indexed by region *r*, tree species s_i, and site class *sc*. Climate is an implicit argument of average volume since the parameters are estimated separately across regions that have different average climates. Figure C.1 below is an example of estimated yield curves for Douglas-fir in western Oregon for different site productivity classes.

Figure C.1: Example of Douglas-fir yield curve, price region 1 in western Oregon by site productivity class



Note: OR_1_DF_12 indicates Doug-fir in site productivity class 1 and 2, in price region 1 in Oregon, for example.

Once we get the coefficient estimates – and suppressing the region and site class notation – we solve for the optimal rotation $T_{s_i}^F$ to maximize the present value of an infinite stream of harvest revenue for species s_i:

$$\overline{J_t^F}\left(s_j, c_t\right) = \frac{P_{s_i} * vol_{s_i}(T_{s_i}^F, c_t)}{\exp\left(\delta * T_{s_i}^F\right) - 1} \tag{C.2}$$

where P_{s_i} is timber price, $vol_{s_i}(T_{s_i}^F, c_t)$ is timber volume for species s_i at time $T_{s_i}^F$, and δ is assumed to be 5%. The optimal rotation $T_{s_i}^F$ gives the maximized present value, which is used to calculate annual rents, and specified as:

$$\overline{rent}_{r(n)s_j t} = \delta * \overline{J_t^F}\left(s_j, c_t\right) \tag{C.3}$$

C.2. Calculation of carbon rents

Following van Kooten et al. (1995), when a carbon price is introduced, the landowners maximize the present value of timber and carbon sequestration benefits over all future rotations:

$$PV = \frac{[P_F * Q_F(T)] - [P_C * (1-s) * Q_C(T)] + [P_C * \{Q_C(T) + r \int_0^T Q_C(t)dt\}]}{\exp(r * T) - 1} \tag{C.4}$$

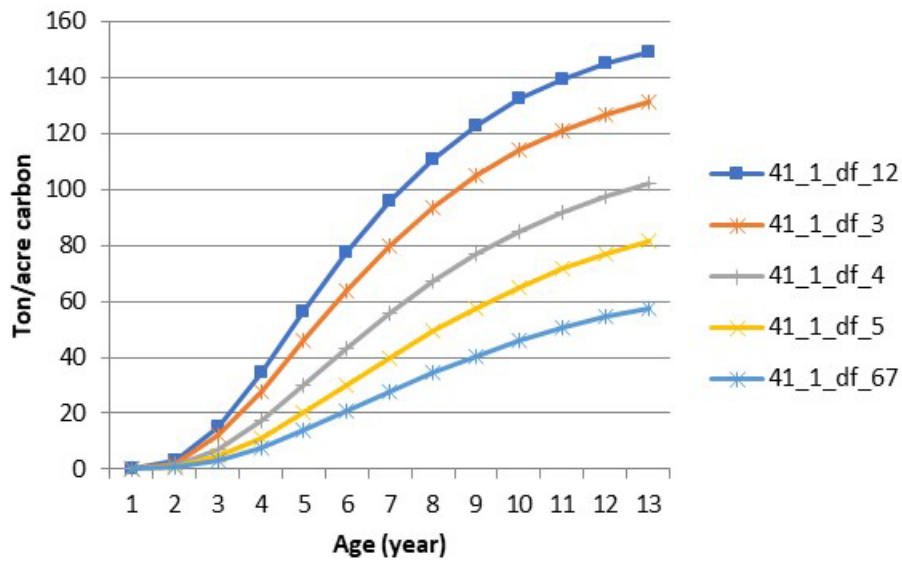
where P_F is the forest price, $Q_F(T)$ is the forest volume, P_C is carbon price, s is the fraction of harvested timber that continues to sequester carbon (assumed to be 0.7, based on Smith et al. (2006)), and $Q_C(T)$ is carbon sequestered at time T. The first term represents the value of timber and the second term represents the cost of carbon released at harvest. The last term is the benefit from carbon sequestration. The timber price remains constant in the future while carbon prices increase from \$15/ton to \$50/ton in 2050, and again from \$50/ton to \$80/ton in 2080. An alternative specification of the carbon price trajectory is to assume the annual growth rate of carbon price (Ekholm, 2016), but this approach requires a recursive formulation of the objective function. We use the original approach with a constant price by van Kooten et al. (1995), which inspired Ekholm (2016), while accounting for increasing carbon prices in discrete steps, rather than a continuous manner. As the value of carbon to society increases, we find that the optimal length of time until trees are harvested increase (van Kooten et al., 1995).

Similar to the yield curves used to calculate land rents, we fit the FIA data[2] on per-acre tons of carbon in the aboveground portion of each plots' trees[3] to Von Bertalanffy (1938) growth equations to estimate coefficients α and β for each species, site productivity class, and region:

$$Q_C(t) = \alpha\{(1 - e\text{^}(-\beta * (\text{Age}))\}\text{^}3 \qquad \text{(C.5)}$$

Using the functional forms for $Q_C(t)$, we solve for the optimal rotation that maximizes the present value of both timber and carbon sequestration benefits over time. Figure C.2 below is an example of fitted carbon sequestration curves for Douglas-fir in western Oregon by site productivity class.

Figure C.2: Sequestered carbon curves by site class, Douglas-fir in western Oregon



Note: 41_1_df_12 indicates Doug-fir in site productivity class 1 and 2 in price region 1 in Oregon.

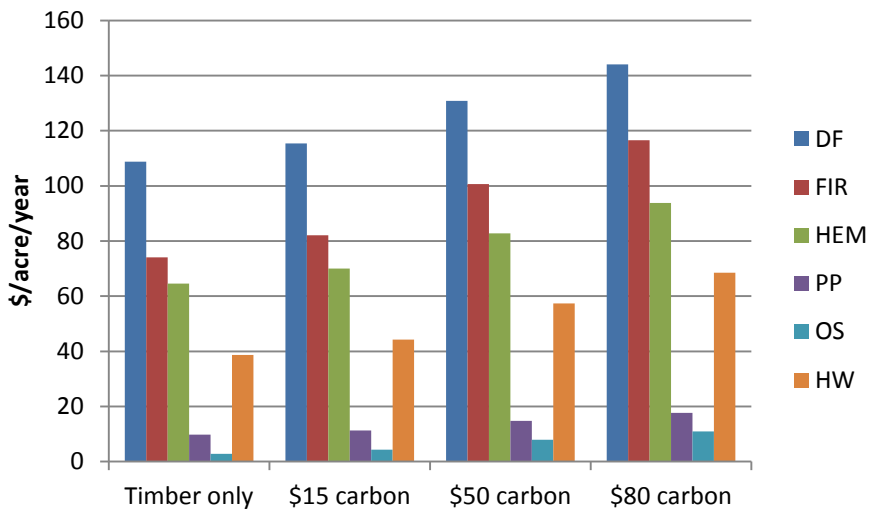
Once the maximum present values are calculated, we multiply them by an interest rate to obtain an annualized carbon rent. Figure C.3 illustrates how carbon rent augments timber rent for the highest site productivity class in Western Oregon (except for Ponderosa Pine, which is based

[2] Ideally the dataset should consist of volume of carbon sequestered and stand age at each species for each condition class. However, as the stand age is recorded at the condition class level in the FIA, not at the species level, we aggregated the carbon sequestration data at the condition class, which is associated with the most dominant species type. The data set is then used to regress the volume of carbon sequestered on age and to generate the carbon yield curves according to the equation (C.5).

[3] We use carbon in the aboveground portion of the tree, excluding foliage, of live trees with a diameter larger than 1 inch, and converted to per acre values. The FIA data set is queried to generate tons of aboveground carbon at each condition class, and then divided by the corresponding acreage to derive per-acre values.

on eastern Oregon data) as an example. Note that benefits from carbon payments depend on the rate of the carbon uptake, which is species, site productivity, and region specific.

Figure C.3: Rents for highest site productivity class in Western Oregon with current timber prices



Note: DF=Douglas-fir, FIR=Fir/Spruce, HEM=Hemlock/Sitka Spruce, PP=Ponderosa Pine, OS=Other softwood, and HW=hardwood. Rents for Ponderosa Pine are based on log prices in eastern Oregon since prices are unavailable for western Oregon.

Appendix D. Incremental volume growth

The incremental growth variables are used to calculate the benefit from waiting in econometric estimation for the harvest decision, $\Delta vol_{nk(s_j)t}$ in equation (8). They are also used to update the stand volume in the landscape simulation described in section 5. The incremental growths are specific to tree species, age, site productivity class, and region. The following steps are used in calculating the incremental growth variables.

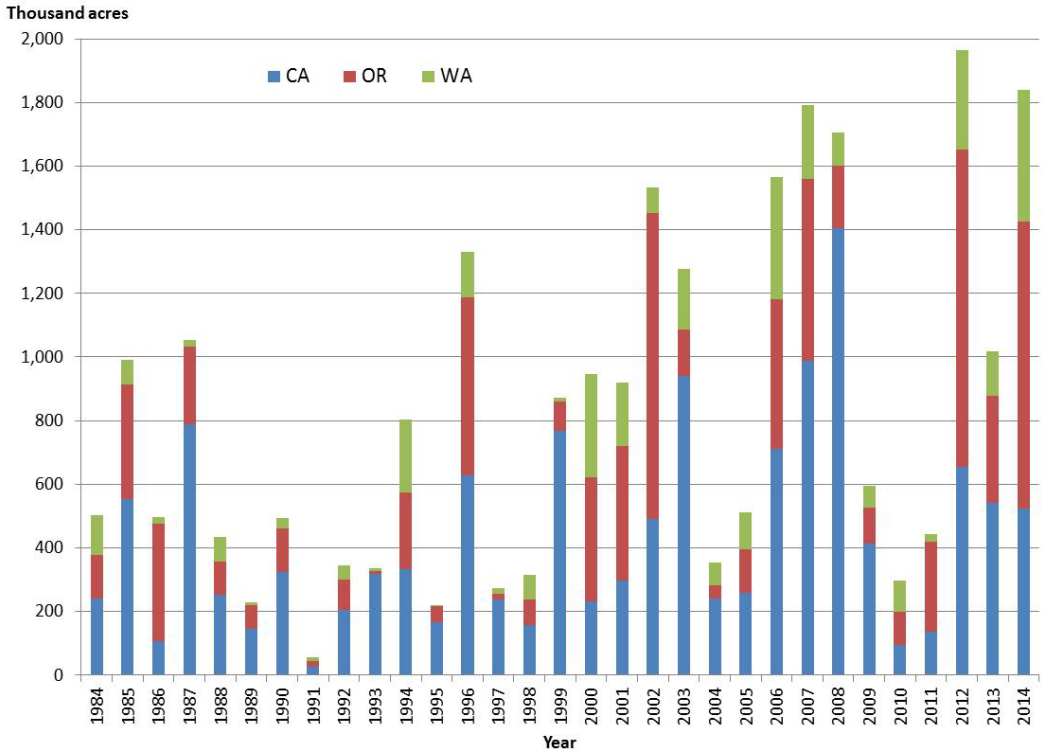
1. Using the bored radial ten-year increment for a 10-year period, average diameter, and average height all recorded in the FIA, we estimate the per-tree average volume in 10 years from today, by applying the equations that translate increment length to volume measures specified in the USDA Forest Service's report (Zhou and Hemstrom, 2010). The estimated equations vary across species and regions. We expand the per-tree volume to per-acre by multiplying with the number of trees per acre.
2. Subtract the current volume recorded in the FIA from the estimated future volume, which provides the estimated incremental volume growth per acre.

3. Aggregate these volumes per species to each plot.
4. For those plots that are missing ten-year increment length data from the FIA, we assign the growth according to the genetic growth data specific to age, species, and region based on Smith et al. (2006). We used the estimated incremental volume growth derived through the steps 1-3 for the unharvested plots. For the clear-cut plots, the incremental growths are derived from estimated growth curves that are fitted with the von Bertlanffy functional form from C.1. The growth parameters α and β are species, site productivity class, and region specific. The fitted curves are also used to update the incremental growth rates for the unharvested plots as older stands have different growth rates, which also vary across species and regions.
5. In the simulation, we also adjust the incremental growth with the downscaled percentage change in net primary productivity based on the 3-PG process model projection by Nicholas Coops and Richard Waring.

Appendix E. Empirical model of wildfire severity

As shown in Figure E.1, total acres burned in wildfires have increased since 1984. They doubled in the most recent decade compared to the 1980's. While burn severity fluctuates considerably, the overall trend is an increasing prevalence of higher severity burns, particularly in California and Washington.

Figure E.1: Historical burned acreage in three Pacific states



The empirical burn severity data that we used is generated by the Monitoring Trends in Burn Severity (MTBS) database, which is a joint product of the Wildland Fire Leadership Council, U.S. Geological Survey, and the USDA Forest Service. It is the main data source for estimating the drivers of burn severity in equation (10). We use the data for all the wildfires that occurred during 2001 – 2014, to be consistent with the FIA dataset that is used for estimation of the forest management model. Table E.1 and Figure E.2 show an overall breakdown of severity by each state and the spatial distribution, respectively.

Table E.1: Summary statistics of historical burn severity 2001-2014[4]

State	Unburned to Low	Low	Moderate	High
CA	19%	34%	26%	19%
OR	20%	51%	20%	9%
WA	18%	45%	23%	14%

[4] Percentages do not add up to 100% as some of the burned acres exhibit "increased greenness," which is not included in the summary.

Figure E.2: Distribution of burn severity 2001-2014

The majority of wildfires have resulted in unburned to low severity, while about a quarter in California and Washington and a fifth in Oregon fall in the moderate category. High burn severity occurs in about 20% of burned area in California and around 10% in Oregon and Washington. A notable feature of Figure E.2 is that there have been very few wildfires in the west of the Cascades in Oregon and Washington, which has by far the wettest climate of the region. There is considerable heterogeneity in burn severity at a spatially fine scale. Using the MTBS historical burn data, we calculated acres burned for each severity, overlaid it on the locations of the FIA plots, and calculated the share of each severity class around each plot using the 2km radius buffers. We selected a 2km radius to accommodate the "fuzziness" of the FIA plots, in which their coordinates were fuzzed within 1 mile (1.6km) of the exact plot location.[5]

We estimate the severity of wildfire as an ordered logit model:

[5] "Fuzzing" of plot location was implemented by FIA to comply with the Food Security Act of 1985 to ensure the privacy of private landowners.

$$SV_i = \beta_0 + \beta_1 priv_i + \beta_2 elev_i + \beta_3 species_i + \beta_4 vol_{it} + \beta_5 c_i + \beta_6 state_i + \varepsilon_i \quad \text{(E.1)}$$

where the dependent variable SV_i is the most dominant burn severity (1: unburned to low, 2: low, 3: moderate, or 4: high) that has occurred in the last ten years within a 2km radius around each plot. It is a severity category that affected the highest share of land around each plot.[6] The same independent variables used in the binary natural disturbance logit equation (6) are used in this ordered logit model. The parameters defining the probabilities of burn severity are estimated outside of the nested logit framework, as coupling an ordered logit model to the nested logit model is computationally challenging and brings up convergence concerns when estimating the nested logit model. Estimating burn severity parameters separately means that we are not letting the severity affect the land value, although we acknowledge that the reflection of severity on the land value would be ideal. Instead, we use the projected probabilities of severity in the simulation to adjust the stand volume, age, and incremental growth. The burn severity parameters to be estimated include all the independent variables in equation (E.1) and three additional parameters of "cut points". The probability of observing an outcome corresponds to the probability that the estimated linear function, plus error terms, is within the range of the cut points estimated for the outcome. The cut points are used to calculate the probability of each severity in the following way:

$$Prob(SV = 1) = Prob(\vartheta x + \varepsilon < cut1) = \frac{1}{1 + \exp(-cut1 + \vartheta x)}$$

$$Prob(SV = 2) = Prob(cut1 < \vartheta x + \varepsilon < cut2) = \frac{1}{1+\exp(-cut2+\vartheta x)} - \frac{1}{1+\exp(-cut1+\vartheta x)} \quad \text{(E.2)}$$

$$Prob(SV = 3) = Prob(cut2 < \vartheta x + \varepsilon < cut3) = \frac{1}{1 + \exp(-cut3 + \vartheta x)} - \frac{1}{1 + \exp(-cut2 + \vartheta x)}$$

$$Prob(SV = 4) = Prob(cut3 < \vartheta x + \varepsilon) = 1 - \frac{1}{1+\exp(-cut3+\vartheta x)}$$

Parameter estimates are given in Table E.2:

[6] As an alternative specification, we also conducted ordered logit estimation with expected severity as a dependent variable. The results show similar results for the coefficient estimates with statistical significance. They are available upon request.

Table E.2: Ordered logit burn severity estimates

	Burn severity (1-4)
Private dummy	-0.13
	(0.16)
Elevation	0.0005***
	(0.00)
Fir dummy	0.02
	(0.24)
Hem dummy	-1.90*
	(1.01)
Ponderosa dummy	0.49***
	(0.16)
Other SW dummy	-0.04
	(0.20)
Hardwood dummy	0.23
	(0.17)
Mean temp.	0.01
	(0.04)
Precipitation	-0.0008***
	(0.00)
Min. temp Dec.	0.09***
	(0.03)
Max. temp Aug.	0.21***
	(0.03)
OR dummy	0.00
	(0.17)
WA dummy	0.49*
	(0.27)
Stand volume	-0.01**
	(0.00)
cut1	9.38***
	(0.85)
cut2	10.31***
	(0.85)
cut3	11.00***
	(0.85)
Log-likelihood	-1981.66

Note: * p<0.1; ** p<0.05; *** p<0.01

Table E.2 indicates that both precipitation and extreme temperatures have significant impacts on the severity of wildfire. A higher elevation is associated with higher severity, and species in wet conditions – Hemlock – are negatively associated with severity, while Ponderosa Pine in the drier region is more prone to severe fires. Although stand volume in the binary natural disturbance model exhibits a positive effect on natural disturbance outcome, it is negatively associated with severity. A denser forest is more likely to be disturbed than a newly harvested forest as a risk of catching fire or infestation by insects increases, but a denser, older forest also can better endure a destructive wildfire as the trees have thicker bark, deeper roots, and fewer branches on lower bole compared to younger forests. Denser forests create less dry microclimate, which also helps withstand a wildfire.

Appendix F. Full data source list and summary statistics

Table F.1: Data sources for variables

Data used in estimation			
Variable	Description	Measurement	Source
Clear-cut	1 if clearcut, 0 if not	Binary	FIA
Partial-cut	1 if patrial cut, 0 if not	Binary	FIA
Disturbed	1 if damage from either fire, insect, disease, or drought, 0 if not	Binary	FIA
Species_fir	1 if dominant tree species type is Fir/Spruce, 0 otherwise.	Binary	FIA
Species_hem	1 if dominant tree species type is Hemlock/Sitka Spruce, 0 otherwise.	Binary	FIA
Species_pp	1 if dominant tree species type is Ponderosa Pine, 0 otherwise.	Binary	FIA
Species_os	1 if dominant tree species type is Other Softwood, 0 otherwise.	Binary	FIA
Species_hw	1 if dominant tree species type is Hardwood, 0 otherwise.	Binary	FIA
Private	1 if private ownership, 0 if state-owned	Binary	FIA
Elevation	Elevation	Feet	FIA
Stand volume	Per acre volume calculated by dividing the total volume by the acreage.	MBF/acre	FIA
Choice_df	1 if Douglas-fir can grow in the plot	Binary	Forest Service
Choice_fir	1 if Fir/Spruce can grow in the plot	Binary	Forest Service
Choice_hem	1 if Hemlock/Sitka Spruce can grow in the plot	Binary	Forest Service
Choice_pp	1 if Ponderosa Pine can grow in the plot	Binary	Forest Service
Choice_os	1 if Other Softwood can grow in the plot	Binary	Forest Service
Choice_hw	1 if Hardwood can grow in the plot	Binary	Forest Service
Timber price	Spot timber price at time of harvest	$/MBF	ODF; CSBE; WSDNR
Rent	Annualized rent for each species, region, and site class. It is derived from solving for the optimal Faustmann rotation.	$/acre	FIA; ODF; CSBE; WSDNR
Clear-cut revenue	Timber price multiplied by the total stand volume	$/acre	FIA; ODF; CSBE; WSDNR
Partial-cut revenue	Timber price multiplied by the partial stand volume	$/acre	FIA; ODF; CSBE; WSDNR
Benefit from waiting	Timber price multiplied by the incremental volume growth.	$/acre	FIA; ODF; CSBE; WSDNR
Burn severity	Wildfire burn severity in scale of 1 (unburned to low), 2 (low), 3 (moderate), and 4 (high).	Categorical	MTBS
Current mean temperature	Mean monthly temperature during growing season	Degrees Celsius	PRISM
Current total precipitation	Total monthly precipitation during growing season	mm	PRISM
Current minimum temperature in Dec.	Monthly 30-year normal minimum December temperature	Degrees Celsius	PRISM
Current maximum temperature in Aug.	Monthly 30-year normal maximum August temperature	Degrees Celsius	PRISM
Expected temperature change	Projected temperature change in the next 30 years	Degrees Celsius	PRISM; NCAR

Data used in simulation			
Variable	Description	Measurement	Source
Projected mean temperature	Projected mean monthly temperature during growing season	Degrees Celsius	NCAR
Projected total precipitation	Projected total monthly precipitation during growing season	mm	NCAR
Projected minimum temperature in Dec.	Projected monthly 30-year normal minimum December temperature	Degrees Celsius	NCAR
Projected maximum temperature in Aug.	Projected monthly 30-year normal maximum August temperature	Degrees Celsius	NCAR
Type of natural disturbance	Historical share of disease, wildfire, and insect damage.	Percentage	FIA
Severity of disturbance	Historical severity of disease and insect damage.	Percentage	FIA
Incremental volume growth	10-year incremental growth	MBF/acre	FIA

Note: Acronyms in the Source column represent Forest Inventory Analysis (FIA), Oregon Department of Forestry (ODF), California State Board of Equalization (CSBE), Washington State Department of Natural Resources (WSDNR), USGS/Forest Service Monitoring Trends in Burn Severity (MTBS), Oregon State University Parameter-elevation Regressions on Independent Slopes Model (PRISM), and U.S. National Center for Atmospheric Research (NCAR).

Table F.2: Mean statistics by species types

Species type	% of total	% naturally disturbed	% clear-cut	% partial-cut	Elevation (feet)	Avg. temp (C)	Total prec. (mm)	Min temp Dec. (C)	Max temp Aug. (C)	Harvest price ($/MBF)
Doug-fir	37%	8%	14%	4%	1,710	12.90	773	-0.68	25.64	458.50
Fir/Spruce	6%	21%	7%	14%	4,578	10.76	579	-4.36	24.91	276.55
Hemlock/Sitka	7%	4%	15%	2%	1,173	12.68	927	0.34	22.74	455.95
Ponderosa Pine	15%	14%	5%	13%	3,805	12.22	378	-4.48	27.88	351.06
Other SW	9%	13%	5%	5%	3,286	12.09	281	-2.85	26.64	355.14
Hardwoods	26%	7%	6%	2%	1,531	14.02	649	1.03	27.97	254.49

Table F.3: Mean characteristics by disturbance occurrence

	Clear-cut		Partial-cut		Naturally disturbed	
Mean characteristics	No	Yes	No	Yes	No	Yes
Count	6,205	640	6,462	383	6,182	663
Avg. temp (Degrees C)	12.89	12.56	12.92	11.91	12.92	12.27
Total precipitation (mm)	606	918	645	469	658	422
Log prices ($/MBF)	363	427	369	372	-	-
Volume (MBF/acre)	14	27	15	11	15	13
Clear-cut revenue ($/acre)	5,946	11,827	6,616	4,475	-	-
Incremental gain from waiting ($/acre)	1,353	1,055	1,346	970	-	-

Appendix G. Econometric parameter estimates and marginal effects for nested logit model

Table G.1: Nested logit econometric parameter estimates

		(1) Replanting following clear-cut	(2) Leaving upon partial-cut
Rent (constant across species)		7.25**	-0.21
		(3.18)	(2.57)
Doug-fir	Rent x temp	-5.65***	-4.64**
		(1.95)	(2.23)
	Rent x precipitation	-0.01**	-0.01
		(0.00)	(0.01)
	Rent x Min temp Dec.	0.00*	-0.003*
		(0.00)	(0.00)
	Rent x Max temp Aug.	1.95***	3.28***
		(0.62)	(0.99)
	Rent x Expected temp. change	-0.01	-0.01
		(0.01)	(0.01)
Fir	Constant	-3.70***	-2.55***
		(0.89)	(0.74)
	Rent x temp	-18.10	-12.30
		(13.86)	(8.22)
	Rent x precipitation	-0.03	-0.05
		(0.02)	(0.03)
	Rent x Min temp Dec.	0.00	-0.01*
		(0.01)	(0.01)
	Rent x Max temp Aug.	13.81**	14.98***
		(6.24)	(4.80)
	Rent x Expected temp. change	-0.12*	-0.15***
		(0.07)	(0.06)
	Elevation	11.49***	7.68***
		(2.08)	(1.57)
Hem	Constant	-1.41***	-1.93**
		(0.44)	(0.82)
	Rent x temp	5.08**	16.35**
		(2.50)	(6.64)
	Rent x precipitation	0.01***	0.02**
		(0.01)	(0.01)
	Rent x Min temp Dec.	0.00**	0.00
		(0.00)	(0.00)
	Rent x Max temp Aug.	-5.16***	-10.09***
		(1.21)	(3.85)
	Rent x Expected temp. change	-0.01	0.00
		(0.01)	(0.02)
	Elevation	2.54	3.34
		(1.85)	(2.62)
Ponderosa	Constant	-2.71***	-0.77*
		(0.67)	(0.42)
	Rent x temp	-0.13	-4.77
		(12.85)	(5.68)
	Rent x precipitation	0.00	-0.05**
		(0.04)	(0.03)
	Rent x Min temp Dec.	-0.02	-0.01**
		(0.01)	(0.00)
	Rent x Max temp Aug.	7.53	5.44*
		(6.31)	(3.19)
	Rent x Expected temp. change	-0.18**	-0.06*
		(0.08)	(0.03)
	Elevation	9.20***	4.84***
		(1.76)	(0.96)
Other SW	Constant	-3.91***	-2.80***
		(0.77)	(0.68)

	Rent x temp	4.63	7.05
		(7.77)	(5.03)
	Rent x precipitation	-0.02	-0.04**
		(0.02)	(0.02)
	Rent x Min temp Dec.	0.00	0.00
		(0.00)	(0.00)
	Rent x Max temp Aug.	-4.05	-1.82
		(3.04)	(1.87)
	Rent x Expected temp. change	0.02	0.00
		(0.03)	(0.02)
	Elevation	8.65***	5.64***
		(1.97)	(1.53)
Hardwoods	Constant	-1.15***	-1.48***
		(0.43)	(0.57)
	Rent x temp	-3.28	-10.01
		(5.69)	(11.84)
	Rent x precipitation	0.00	-0.05
		(0.01)	(0.03)
	Rent x Min temp Dec.	0.00	0.01
		(0.00)	(0.01)
	Rent x Max temp Aug.	1.74	4.15
		(2.67)	(5.03)
	Rent x Expected temp. change	-0.02	0.03
		(0.03)	(0.05)
	Elevation	1.16	1.82
		1.46	(1.54)

(3) Natural disturbance (1=disturbed, 0=not)		(4) Harvest	
Constant	-2.78***	Clear-cut constant	-2.34***
	(0.46)		(0.24)
Private dummy	-0.46***	Clear-cut revenue	10.89***
	(0.08)		(1.24)
Elevation	2.43***	Partial cut constant	-3.07***
	(0.43)		(0.42)
Fir dummy	0.14	Partial cut revenue	6.21***
	(0.09)		(1.95)
Hem dummy	0.03	No-cut benefit waiting	10.82***
	(0.16)		(1.05)
Ponderosa dummy	-0.13	Clear-cut IV	0.66***
	(0.08)		(0.15)
Other SW dummy	0.23***	Partial cut IV	1.50***
	(0.09)		(0.28)
Hardwood dummy	0.32***	Disturbance IV	11.32***
	(0.09)		(1.63)
Mean temp.	0.03		
	(0.02)		
Precipitation	-2.86***		
	(0.44)		
Min. temp Dec.	-0.05***		
	(0.02)		
Max. temp Aug.	0.00		
	(0.02)		
OR dummy	-0.31***		
	(0.08)		
WA dummy	-0.23*		
	(0.13)		
Stand volume	0.01***		
	(0.00)		
Log-likelihood	-5854.16		

Note: Standard errors in parentheses; (* p<0.1; ** p<0.05; ***p<0.01)

Table G.2: Key estimated average marginal effects

Change in variable	Replanting Douglas-fir		Replanting Fir/Spruce		Replanting Hemlock/Sitka Spruce		Replanting Ponderosa		Replanting Other Softwoods		Replanting Hardwood		Natural Disturbance		Clear-cut	
	Avg. ME	Avg. t value	Avg. ME	Avg. t value	Avg. ME	Avg. t value	Avg. ME	Avg. t value	Avg. ME	Avg. t value	Avg. ME	Avg. t value	Avg. ME	Avg. t value	Avg. ME	Avg. t value
Doug-fir rent up by $10																
CA	2.9%***	3.02	-0.2%*	-1.66	0.0%	-0.86	-1.4%**	-2.45	-0.5%*	-1.76	-0.8%*	-1.93	-	-	0.2%*	1.92
E OR	5.0%***	4.00	-1.4%***	-2.94	-0.1%*	-1.84	-2.2%***	-3.00	-1.0%**	-2.29	-0.4%**	-2.41	-	-	0.2%**	2.29
E WA	7.1%***	3.89	-1.4%**	-2.38	-0.4%**	-2.30	-2.4%***	-2.93	-1.0%**	-2.32	-2.0%***	-2.72	-	-	0.3%**	2.50
W OR	3.6%***	4.21	-0.4%	-1.22	-0.9%***	-2.61	-0.4%*	-1.70	-0.2%	-1.57	-1.7%***	-3.18	-	-	1.3%***	3.26
W WA	3.5%***	3.74	-0.1%	-1.15	-1.4%***	-2.82	0.0%	-1.51	-0.1%	-1.61	-1.9%***	-3.04	-	-	0.6%***	2.67
Average	4.0%***	3.75	-0.5%*	-1.69	-0.6%***	-2.59	-1.1%**	-2.51	-0.5%*	-1.94	-1.4%***	-2.74	-	-	0.01***	2.60
Hardwood rent up by $10																
CA	-1.6%	-1.20	-0.1%	-1.01	0.0%	-0.76	-1.6%	-1.26	-0.4%	-1.11	3.7%	1.33	-	-	0.2%	1.11
E OR	-0.5%*	-1.68	-0.3%*	-1.67	0.0%	-1.39	-0.9%*	-1.69	-0.3%	-1.52	2.1%*	1.89	-	-	0.1%	1.56
E WA	-2.8%	-1.61	-0.8%	-1.38	-0.3%	-1.32	-1.7%	-1.56	-0.7%	-1.42	6.3%*	1.73	-	-	0.3%	1.23
W OR	-3.8%	-1.64	-0.2%	-0.88	-0.5%	-1.41	-0.2%	-1.12	-0.1%	-1.05	4.7%*	1.68	-	-	0.4%	1.37
W WA	-4.0%*	-1.85	-0.1%	-0.90	-1.2%*	-1.69	0.0%	-1.13	-0.1%	-1.18	5.3%*	1.89	-	-	0.5%	1.35
Average	-2.7%	-1.59	-0.2%	-1.05	-0.4%	-1.50	-0.8%	-1.34	-0.3%	-1.22	4.5%*	1.66	-	-	0.00	1.28
Avg. temp up by 3 C°																
CA	-4.2%	-1.35	-1.5%	-0.89	0.6%*	1.79	1.8%	0.25	2.2%	0.76	1.1%	0.70	1.1%	1.26	-0.7%	-1.21
E OR	-1.3%	-0.58	-3.8%	-1.20	0.2%	1.29	1.3%	0.21	3.3%	0.82	0.2%	0.42	1.4%	1.26	-0.7%	-1.15
E WA	-2.8%	-1.26	-2.8%	-1.00	1.1%	1.72	2.5%	0.70	2.1%	1.06	-0.2%	0.01	1.2%	1.26	-0.7%*	-1.65
W OR	-29.8%***	-3.79	-0.9%	-0.30	22.5%***	3.34	2.2%	0.51	1.2%	0.78	4.9%	0.72	0.4%	1.23	-4.9%	-1.54
W WA	-29.9%***	-4.35	-0.2%	-0.23	31.8%***	3.21	0.0%	0.53	0.6%	0.49	-2.3%	-0.37	0.6%	1.24	-4.4%	-1.02
Average	-15.7%***	-2.74	-1.5%	-0.61	13.0%***	3.04	1.5%	0.40	1.7%	0.82	0.9%	0.32	0.9%	1.25	-2.6%	-1.30
Precipitation down by 20%																
CA	0.1%	0.53	0.1%	0.46	-0.1%**	-2.48	-0.2%	-0.16	0.1%	0.16	-0.1%	-0.72	0.9%***	5.56	-0.5%***	-3.43
E OR	0.0%	-0.08	0.1%	0.59	0.0%	-1.60	-0.1%	-0.44	0.1%	0.37	0.0%	-0.70	0.3%***	5.64	-0.1%***	-4.17
E WA	0.0%	0.42	0.1%	0.68	-0.1%**	-2.18	-0.1%	-0.46	0.0%	0.37	0.0%	-0.23	0.5%***	5.42	-0.2%***	-4.61
W OR	3.7%*	1.95	0.3%	0.46	-3.2%***	-3.43	-0.1%	-0.21	0.0%	0.00	-0.7%	-1.01	0.6%***	6.29	-0.1%	-0.90
W WA	3.0%**	2.30	0.0%	0.40	-3.1%***	-3.50	0.0%	-0.40	0.0%	0.46	0.0%	-0.04	0.6%***	5.37	-0.7%**	-2.20
Average	1.6%	1.32	0.1%	0.51	-1.5%***	-3.29	-0.1%	-0.29	0.1%	0.26	-0.2%	-0.55	0.6%***	5.68	-0.4%***	-2.80
Exp. temp up by 1 C°																
CA	2.6%	0.81	-1.0%	-0.52	0.1%	0.28	-15.7%**	-2.00	9.1%	1.52	5.0%	1.48	-	-	-	-
E OR	4.9%	1.50	-3.9%	-0.87	0.2%	1.26	-18.6%**	-2.05	15.9%*	1.71	1.5%	1.41	-	-	-	-
E WA	5.0%	1.29	-3.9%	-1.00	0.6%	1.07	-8.2%*	-1.80	6.0%	1.41	0.5%	0.23	-	-	-	-
W OR	-6.1%*	-0.40	-1.6%	-0.37	2.1%	0.44	-2.6%	-1.10	2.8%	0.94	5.4%	0.60	-	-	-	-
W WA	-3.3%**	-0.22	-0.4%	-0.37	1.7%	0.33	0.0%	-0.84	1.7%	0.84	0.4%	0.01	-	-	-	-
Average	-0.2%	0.34	-1.7%	-0.58	1.0%	0.45	-8.2%*	-1.81	6.2%	1.40	3.0%	0.68	-	-	-	-

Note: * p<0.1; ** p<0.05; *** p<0.01

Appendix H. Plant viability score (green-colored plots are viable in our definition of >0.3)

Douglas-fir Hardwood

Appendix I. Robustness checks with alternative econometric specifications

There are a number of reasonable specifications in which to estimate the econometric parameters. In this section, we examine the robustness of the model to multiple alternative specifications. Multiple alternative specifications are considered here: (1) Sample includes privately owned plots only (i.e., drop state-owned plots); (2) Use average temperature difference between December and August in lieu of minimum temperature and maximum temperature; (3) Use natural disturbance equation in lieu of "Disturbance IV" in the harvest model since the inclusive values from the disturbance nest may not be justified as a maximum utility measure; (4) Use expected temperature increase over the next 70 years, instead of 30 years; (5) Add

"Distance to the closest mill" variable to the replanting model; (6) Swap climate variables for some plots within each county to examine the importance of the FIA's characteristic of randomly swapping the location of some plots within counties[7]; (7) Add interaction term between rent and California dummy variable to account for the fact that the timber prices in California are stumpage prices while those in Oregon and Washington are pond prices inclusive of logging costs.; and (8) Exclude stand volume variable in the natural disturbance equation to test the endogeneity concern that omitted variable such as fire prevention activities and the stand volume could be correlated.

We also evaluate the potential for omitted variables to induce endogeneity bias in the parameter estimates. Endogeneity problems arise if any unobservable variables are correlated with the included explanatory variables. In our econometric specification, a possible candidate for an endogenous unobservable factor is plot-specific levels of infrastructure; e.g., access to a forest road that would lower costs. It's plausible that timber infrastructure – like access to a road – is correlated with climate if road builders explicitly considered good timber-growing climate when designing road infrastructure. Another potential culprit for an omitted variable correlated with climate is ownership – private industrial owner or non-industrial private owner – which could affect harvest and replanting decisions and potentially be correlated with climate if industrial landowners were more likely to take ownership of prime timber-growing conditions.

We test whether these omitted variables – access to road and ownership types – are correlated with the explanatory variables. Since detailed private owner types are not publicly available, we use a proxy to distinguish these different types of ownerships. Previous literature found that forestlands managed for commercial/industrial timber production are negatively correlated with population densities (Wear et al., 1999). Another study supports this conclusion that population growth and urban expansion are correlated with reduced forest management and investment on private forestlands in western Oregon (Kline et al., 2004). The data for population density, however, is available only at the county level. As a proxy for population density, we use a satellite image of night-time lights. A previous study found a strong correlation between population density and night-time lights (Sutton, 1997). The data from the National Oceanic and

[7] Up to 20% of the private plots' coordinates are swapped with another similar private plot within the same county. Swapped plots are chosen to be similar based on attributes such as forest type and stand-size class and may induce some measurement error into the climate variables. We ran 50 different versions of randomly swapping 20% of plots.

Atmospheric Administration (NOAA) contains the lights from cities, towns, and other sites with persistent lighting, ranging from 1 to 63. Neither night-time lights nor distance to road appears to be correlated with explanatory variables.[8] We also estimated the full nested logit model with road distance and nighttime lights, and estimated the marginal effect of a few key variables to examine whether they are sensitive to inclusion.[9] Results are included in the Tables I1 through I3 as (9) including night-time light; and (10) including distance to road.

Tables I.1 through I.3 present a comparison of key marginal effects of our base specification and the nine alternative specifications described above.[10] Except for an effect of an increase in temperature on replanting Douglas-fir, our estimation results are quite robust across the suite of estimators used to fit the models. Marginal effects of temperature change, however, show similar negative impacts on choosing Douglas-fir, and the degree of effects are in the relatively narrow range of -9% to -18%.

[8] For example, correlations between night-time lights and climate variables are: 0.15 (temp), -0.07 (precip), 0.10 (min. temp), -0.00 (max. temp). Correlation between distance to road and climate is negligible.
[9] Inclusion of both variables together resulted in non-convergence of parameter estimates. As a compromise, we present the results in which each omitted variable is included.
[10] Full sets of parameter estimates under each alternative specification and other marginal effects, respectively, are available upon request.

Table I.1: Comparison of marginal effects on replanting Douglas-fir

Change in variables	Base	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Doug-fir rent up by $10	4.0%***	4.3%***	3.9%***	5.0%***	4.0%***	4.0%***	4.1%***	3.0%***	3.9%***	3.2%	3.3%
	(3.74)	(3.60)	(4.05)	(4.29)	(3.92)	(3.71)	(3.82)	(2.76)	(3.70)	(0.69)	(0.72)
Avg. temp up by 3 C	-15.7%***	-17.8%***	-9.1%**	-14.8%**	-15.1%**	-17.2%***	-14.5%**	-16.3%***	-15.6%***	-16.3%***	-17.7%***
	(-2.73)	(-3.06)	(-2.37)	(-2.52)	(-2.47)	(-3.02)	(-2.45)	(-2.82)	(-2.62)	(-2.61)	(-3.02)
Precip. down by 20%	1.6%	1.8%	1.0%	1.4%	1.5%	1.8%	1.8%*	1.7%	1.6%	0.9%	1.0%
	(1.37)	(1.56)	(1.26)	(1.03)	(1.20)	(1.55)	(1.75)	(1.46)	(1.33)	(0.20)	(0.21)

Table I.2: Comparison of marginal effects on clear-cut

Change in variables	Base	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Doug-fir rent up by $10	0.6%***	0.6%***	0.5%***	0.6%***	0.6%***	0.6%***	0.6%***	0.4%**	1.1%***	0.4%	0.4%
	(2.65)	(2.42)	(2.85)	(3.16)	(2.87)	(2.72)	(2.76)	(1.99)	(3.51)	(0.36)	(0.33)
Avg. temp up by 3 C	-2.5%	-2.9%	-2.7%**	-2.5%	-2.5%	-2.3%	-3.8%**	-2.5%	-2.8%	-2.9%	-2.8%
	(-1.32)	(-1.51)	(-1.98)	(-1.23)	(-1.34)	(-1.15)	(-2.08)	(-1.23)	(-1.37)	(-0.93)	(-0.96)
Precip. down by 20%	-0.4%***	-0.4%***	-0.3%***	-0.3%***	-0.3%***	-0.4%***	-0.2%**	-0.2%***	0.1%	-0.5%	-0.5%
	(-2.89)	(-2.73)	(-3.19)	(-3.10)	(-2.81)	(-2.85)	(-2.37)	(-2.62)	(-0.97)	(-0.31)	(-0.32)

Table I.3: Comparison of marginal effects on natural disturbance

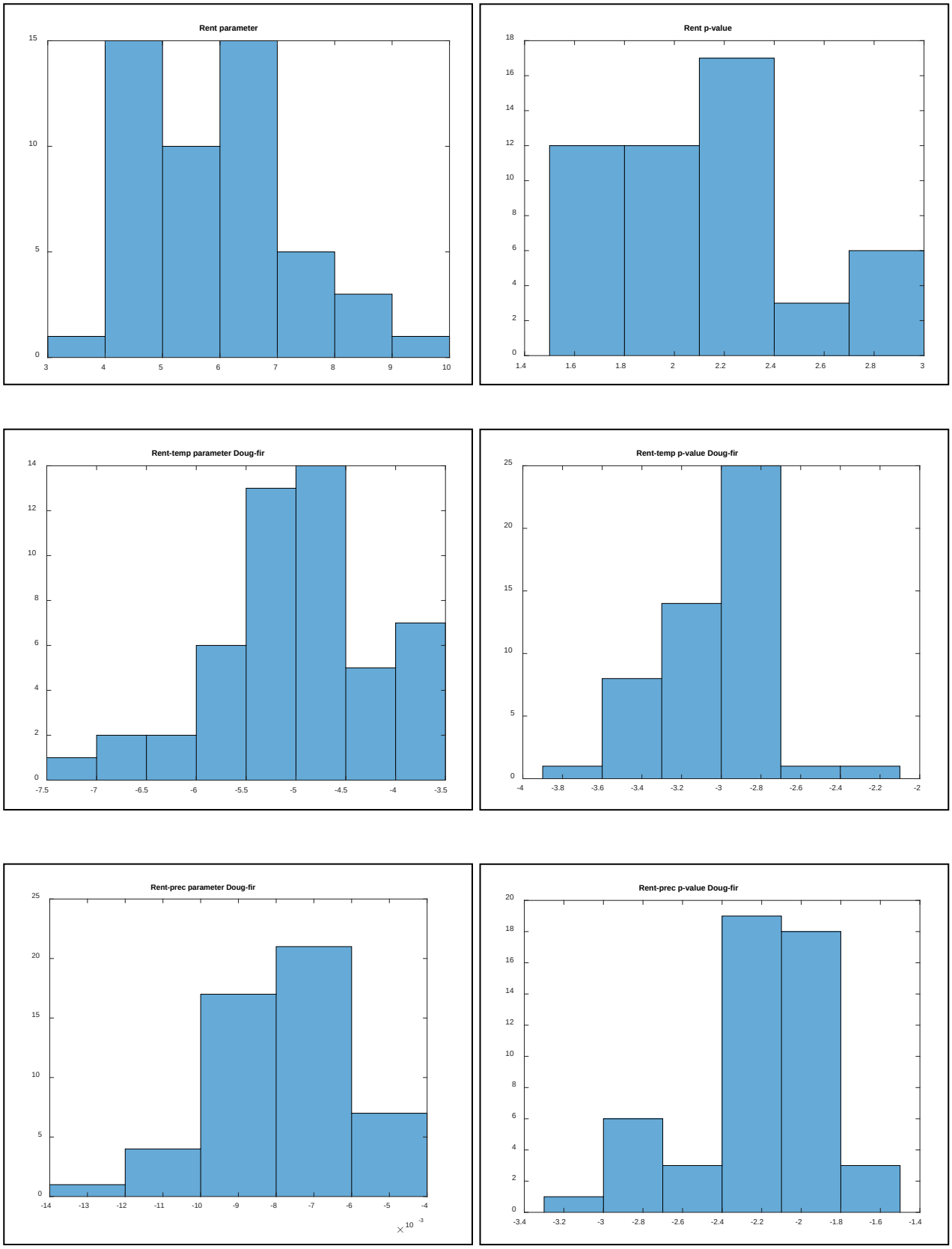
Change in variables	Base	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Doug-fir rent up by $10	-	-	-	-	-	-	-	-	-	-	-
Avg. temp up by 3 C	0.9%	1.1%*	0.4%	0.7%	0.7%	1.1%	1.1%	0.8%	0.9%	0.9%	0.9%
	(1.31)	(1.60)	(0.84)	(0.79)	(1.09)	(1.50)	(1.55)	(1.14)	(1.45)	(1.32)	(1.35)
Precip. down by 20%	0.6%***	0.6%***	0.6%***	0.6%***	0.6%***	0.6%***	0.6%***	0.6%***	0.5%***	0.6%***	0.6%***
	(5.77)	(5.25)	(6.35)	(5.96)	(5.79)	(5.85)	(5.77)	(5.45)	(5.13)	(5.52)	(5.59)

Note: Average t value in parenthesis**.** * p<0.1; ** p<0.05; *** p<0.01

(1)-(10) in the column headers correspond to the sensitivity scenarios described in page 18 - 20.

To further evaluate the FIA's process of randomly "swapping" some plots within counties, we present a histogram of the parameter estimates from a Monte Carlo approach to robustness analysis. In order to maintain the privacy of owners, up to 20 percent of the private plots' coordinates are swapped with another similar private plot within the same county in FIA. Swapped plots are chosen to be similar based on attributes such as forest type and stand-size class. Swapping of FIA plots indicates that climate variables that are associated with management decisions might have measurement error. To test the robustness of our estimates, we repeatedly swapped the climate variables for some plots that have the same forest species type and stand-size class within each county. To account for the upper limit of 20 percent, we draw a uniform random number for each plot and swap plots when the random number is less than or equal to 0.2. We ran 50 different versions of swapping by randomly choosing the plots to be swapped. For each of the 50 different swapped versions of the climate variables we re-estimate the nested logit model, and results (including associated p values) are presented in Figure I1 as histograms for a few key parameters: coefficients for rent, rent x temperature interaction, and rent x precipitation interaction, all in the replanting nest. The absolute differences in climate variables due to the swapping are 0.67 ºC for temperature and 111 mm for precipitation on average. Notice that this robustness check assumes the most pessimistic scenario of swapping the plots at the upper bound of 20 percent, while the FIA swapping only occurs "up to 20 percent". Our results remain robust.

Figure I.1: Variations in parameter estimates and p values across randomized swapping (6)



Appendix J. Projection of future tree growth

Figure J.1: Change in net primary productivity due to climate change (RCP 8.5) by 2090 relative to 1990 (percentage)

Source: 3-PG NPP projection available from https://databasin.org
3PG model run is based on Coops et al. 2010.

Appendix K. Discrete effect of 90-year climate and carbon price path on the probability of extensive margin adaptation

Table K.1: Discrete effect by initial forest type

Region	Initial forest type	Number of plots	Average discrete effect of climate change (RCP 8.5)	Average discrete effect of carbon price
West California	Douglas-fir	189	6.6%	5.0%
	Fir/Spruce	97	3.3%	-0.3%
	Hemlock/Sitka	9	-0.6%	-0.4%
	Ponderosa Pine	255	0.1%	1.3%
	Other softwood	274	0.3%	0.3%
	Hardwood	660	0.8%	-1.0%
East California	Douglas-fir	42	13.1%	2.8%
	Fir/Spruce	55	6.2%	0.3%
	Hemlock/Sitka	1	22.8%	13.5%
	Ponderosa Pine	120	-3.5%	-0.2%
	Other softwood	17	7.8%	7.1%
	Hardwood	158	-0.8%	1.1%
West Oregon	Douglas-fir	1012	10.6%	6.9%
	Fir/Spruce	35	-6.7%	-2.1%
	Hemlock/Sitka	115	-3.6%	0.2%
	Ponderosa Pine	36	-8.8%	2.4%
	Other softwood	9	-11.4%	0.2%
	Hardwood	409	-16.5%	-4.3%
East Oregon	Douglas-fir	92	6.9%	1.3%
	Fir/Spruce	84	3.5%	0.8%
	Hemlock/Sitka	1	-2.5%	-3.3%
	Ponderosa Pine	289	1.2%	1.4%
	Other softwood	263	4.9%	0.1%
	Hardwood	40	6.4%	1.1%
West Washington	Douglas-fir	791	1.9%	4.2%
	Fir/Spruce	51	-10.2%	-1.0%
	Hemlock/Sitka	342	-2.7%	1.2%
	Ponderosa Pine	0	NA	NA
	Other softwood	11	-11.7%	-0.3%
	Hardwood	394	-15.1%	-3.8%
East Washington	Douglas-fir	382	5.4%	3.2%
	Fir/Spruce	96	-0.3%	1.9%
	Hemlock/Sitka	29	2.1%	3.4%
	Ponderosa Pine	339	5.9%	3.7%
	Other softwood	62	3.4%	1.1%
	Hardwood	86	4.3%	-0.4%

Table K.2: Discrete effect by final forest type

	Discrete effect of a 90-year path of climate change (RCP 8.5)					
	Switch to Douglas-fir	Switch to Fir/Spruce	Switch to Hemlock/Sitka Sprue	Switch to Ponderosa Pine	Switch to Other Softwood	Switch to Hardwoods
West California	-1.3%	1.2%	-0.2%	1.7%	-0.9%	0.8%
East California	-2.4%	0.8%	0.0%	3.5%	-0.8%	0.1%
West Oregon	-5.5%	2.5%	-3.8%	1.3%	0.6%	6.8%
East Oregon	-0.8%	3.2%	0.1%	1.0%	-1.2%	1.4%
West Washington	-5.6%	0.3%	-4.1%	0.0%	1.6%	3.9%
East Washington	-0.2%	1.9%	0.5%	1.0%	-0.1%	1.7%
	Discrete effect of a 90-year path of increasing carbon price					
	Switch to Douglas-fir	Switch to Fir/Spruce	Switch to Hemlock/Sitka Spruce	Switch to Ponderosa Pine	Switch to Other Softwood	Switch to Hardwoods
West California	-1.3%	0.2%	0.0%	0.1%	0.5%	1.0%
East California	-0.6%	-0.1%	0.0%	1.2%	0.1%	0.4%
West Oregon	-2.0%	0.4%	-0.3%	0.7%	-0.1%	4.6%
East Oregon	0.0%	-0.4%	-0.1%	0.0%	1.4%	0.0%
West Washington	-2.1%	-0.2%	-0.9%	0.0%	1.3%	3.2%
East Washington	-0.6%	-0.9%	-0.3%	-0.5%	1.6%	3.5%

References for supplementary appendix

Coops, Nicholas C, Robbie A Hember, and Richard H Waring. 2010. Assessing the impact of current and projected climates on Douglas-Fir productivity in British Columbia, Canada, using a process-based model (3-PG). *Canadian Journal of Forest Research* 40 (3): 511–24.

Ekholm, Tommi. 2016. Optimal forest rotation age under efficient climate change mitigation. *Forest Policy and Economics* 62: 62–68.

Kline, Jeffrey D, David L Azuma, and Ralph J Alig. 2004. Population growth, urban expansion, and private forestry in western Oregon. *Forest Science* 50 (1): 33–43.

Krinsky, I., Robb, A.L., 1986. On Approximating the Statistical Properties of Elasticities. Rev. Econ. Stat. 68, 715–719.

Lewis, David J, and Andrew J Plantinga. 2007. Policies for habitat fragmentation: combining econometrics with GIS-based landscape simulations. Land Economics 83 (2): 109–127.

Lewis, David J. 2010. An economic framework for forecasting land-use and ecosystem change. Resource and Energy Economics 32 (2): 98–116.

Smith, James E, Linda S Heath, Kenneth E Skog, and Richard A Birdsey. 2006. Methods for calculating forest ecosystem and harvested carbon with standard estimates for forest types of the United States. *USDA Forest Service General Technical Report* NE-343.

Sutton, Paul. 1997. Modeling population density with night-time satellite imagery and GIS. *Computers, Environment and Urban Systems* 21 (3–4). Remote Sensing of Urban Systems: 227–44.

USGS, and USDA Forest Service. Monitoring Trends in Burn Severity (MTBS). http://mtbs.gov/.

van Kooten, G Cornelis, Clark S Binkley, and Gregg Delcourt. 1995. Effect of Carbon Taxes and Subsidies on Optimal Forest Rotation Age and Supply of Carbon Services. *American Journal of Agricultural Economics* 77 (2): 365.

von Bertalanffy, L. 1938. A quantitative theory of organic growth (inquiries on growth laws II). *Human Biology* 10 ((2)): 181–213.

Wear, David N, Rei Liu, J Michael Foreman, and Raymond M Sheffield. 1999. The effects of population growth on timber management and inventories in Virginia. *Forest Ecology and Management* 118 (1–3): 107–15.

Zhou, Xiaoping, and Miles A Hemstrom. 2010. *Timber volume and aboveground live tree biomass estimations for landscape analyses in the Pacific Northwest*. Pacific Northwest Research Station General Technical Report. U.S. Department of Agriculture, Forest Service.