Supplementary Index (Johnson and Lewis):

A1: Net Returns to Forestry and Stumpage Price Data:

We use a county-level data set of the annualized net economic returns to forestland for each year from 1998-2014 (Mihiar and Lewis, 2021). To avoid the identification issues that stem from a lack of within-county climate variation, we aggregate these net returns data to a regional level for each of these two categories of forests. Additionally, net returns data do not exist for every forest group in every county. This could either be because price data was not collected or reported in a county or because there is minimal to no market activity for a particular forest group in a county. In other words, either no, or a very small amount of trees of that forest group are being bought and sold in that county (Mihiar and Lewis 2021). Regions are defined by the FIA survey groups. There are 21 regions in our data set, with an average of 20 counties per region. This aggregation of net returns is advantageous for two main reasons: first, the within-region climate variation is now much greater than within-county climate variation; second, we lose fewer observations as a result of missing county-level net returns data. As discussed in the main text, we use these data to construct a measure of expected net returns to each replanting choice by taking an average of the net returns from the five years preceding time t. Ultimately, this results in expected net returns data for the years 2002-2014 which varies across regions and the two planting choices.

Additionally, we use the recorded stumpage price data from this dataset to calculate the marginal costs and benefits of harvesting used to estimate our harvest model. Prices are recorded at the county-level annually from 1998-2014 and matched to each tree species group. In the case of our study area, pine forests are the more valuable forest type with average net returns more than double the per acre value of hardwood forests (Mihiar and Lewis 2021).

A2: Additional Simulation Results

We run the simulation as described in Section 7.1 in the main text for six additional sample plots in Kentucky, Tennessee, and Virginia (two plots per state). For each state, there is a sample plot with a climate that is about 2 standard deviations below the state average. These plots have cooler and drier climates, which we refer to as the "low climate" plots. The second plot has a climate that is about 2 standard deviations above the state climate. These plots have warmer and wetter climates, which we refer to as the "high climate" plots. Current and future climate variables for these plots are presented in Table A7. Our findings hold across these additional sample plots, with one exception: The underestimation of adaptation speed that results from ignoring weather variability is not observed in the "high climate" plots in Tennessee and Virginia.

Simulation results are presented in Figures A2.2 through A2.5. Results are consistent with two key findings discussed in the main text and are briefly summarized below:

1. All else equal, increased weather variability slows adaptation.

These results are consistent across the six additional sample plots. When more *days<0* are substituted (Fig. A2.2 and A2.3, bottom row, blue and green lines), the speed of adaptation diminishes relative to the Hadley scenario (orange line). Under the Hadley projections, the probability of climate adaptation to pine forests by 2100 is 11.4%, 6.6% and 4.2% (11.8%, 8.4%, and 5.5%) for the high climate (low climate) plots in Kentucky, Tennessee, and Virginia respectively. When the *days<0* projected by the CCSM model (the model which projects the most *days<0* by 2100) are substituted, the probability of climate adaptation is 6.4%, 2.1% and 2.8% (2.9%, 4.7%, and 1.2%) for the high climate (low climate) plots respectively.

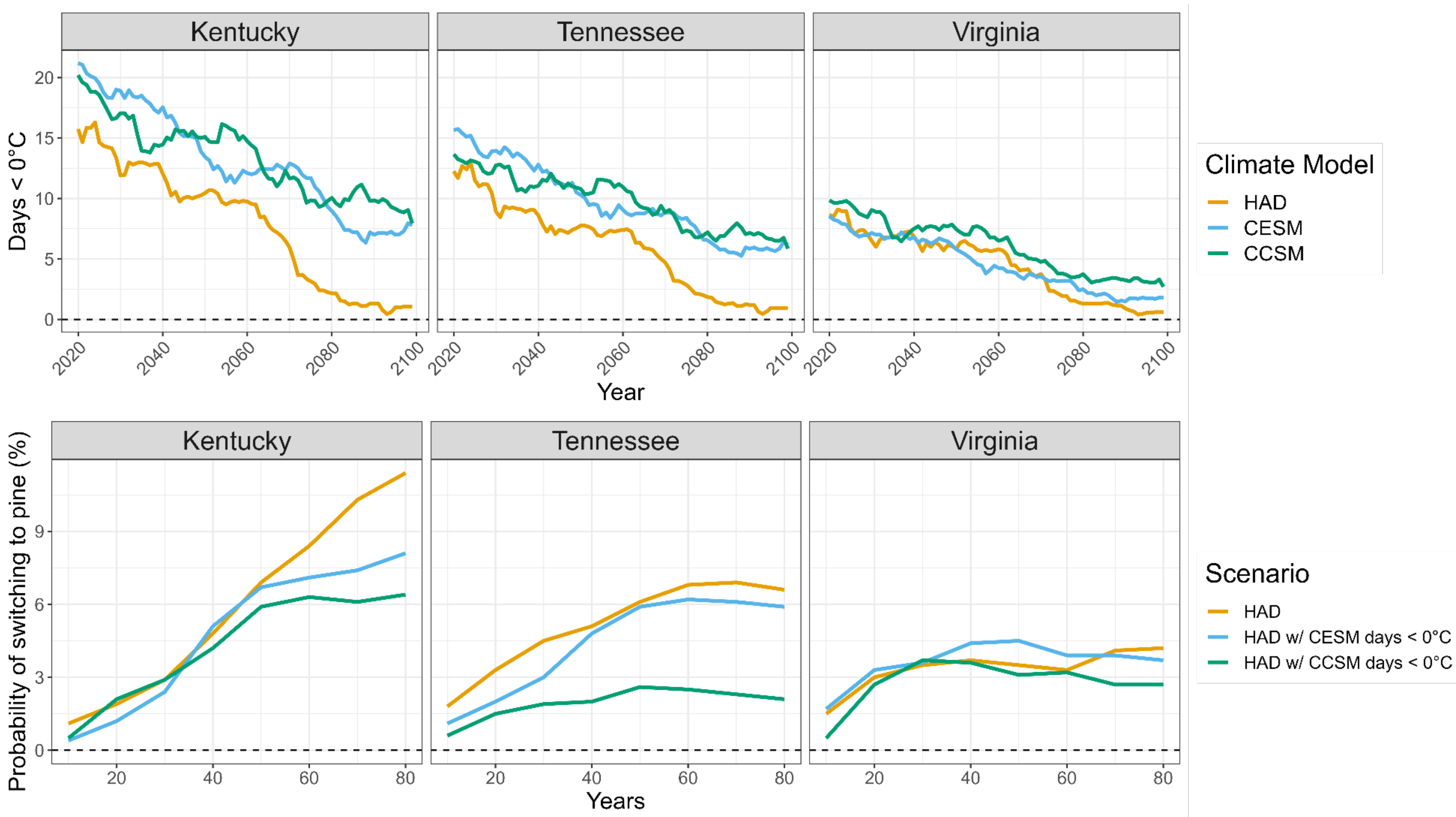

Figure A2.2 "High climate" plots: Top row: projected *days<0* for each of our three sample plots using the three different climate models. **Bottom row:** Simulation results. The orange line is the simulated adaptation path using the Hadley climate model. The blue (green) line is the simulated path of the Hadley model, but with the *days<0* projected by the CESM (CCSM) model.

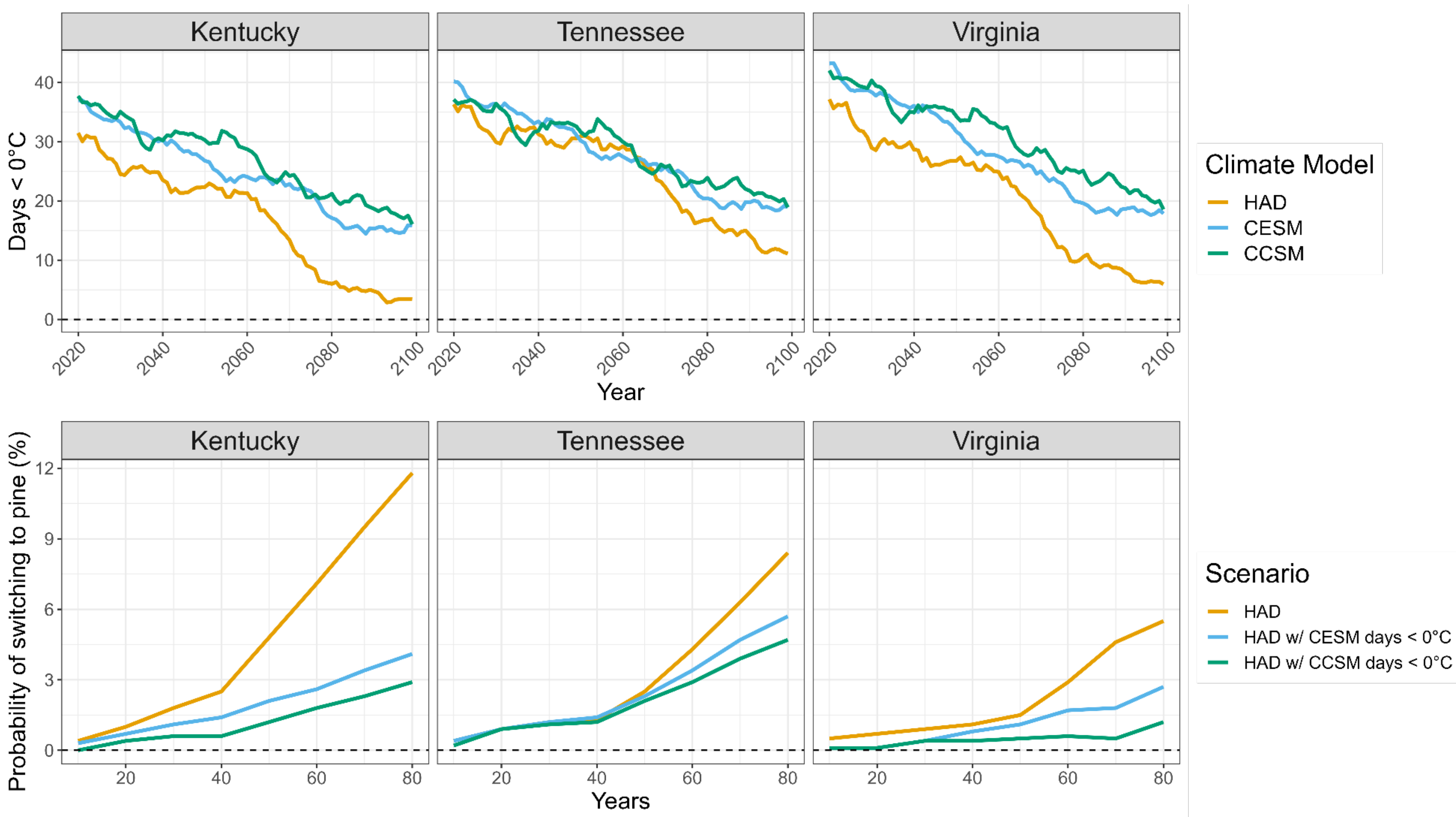

Figure A2.3 "Low climate" plots: Top row: projected *days<0* for each of our three sample plots using the three different climate models. **Bottom row:** Simulation results. The orange line is the simulated adaptation path using the Hadley climate model. The blue (green) line is the simulated path of the Hadley model, but with the *days<0* projected by the CESM (CCSM) model.

2. Ignoring weather variability leads to a smaller range of adaptation paths and underestimates adaptation speed.

This finding holds for the additional sample plots with one exception. While all plots exhibit a smaller range of adaptation paths when weather variability is ignored (blue band), this range is not significantly lower than the range of adaptation paths that control for weather variability (orange band) for the "high climate" plots in Tennessee and Kentucky. Figures A2.4 ("high climate" plots) and A2.5 ("low climate" plots) present these adaptation paths.

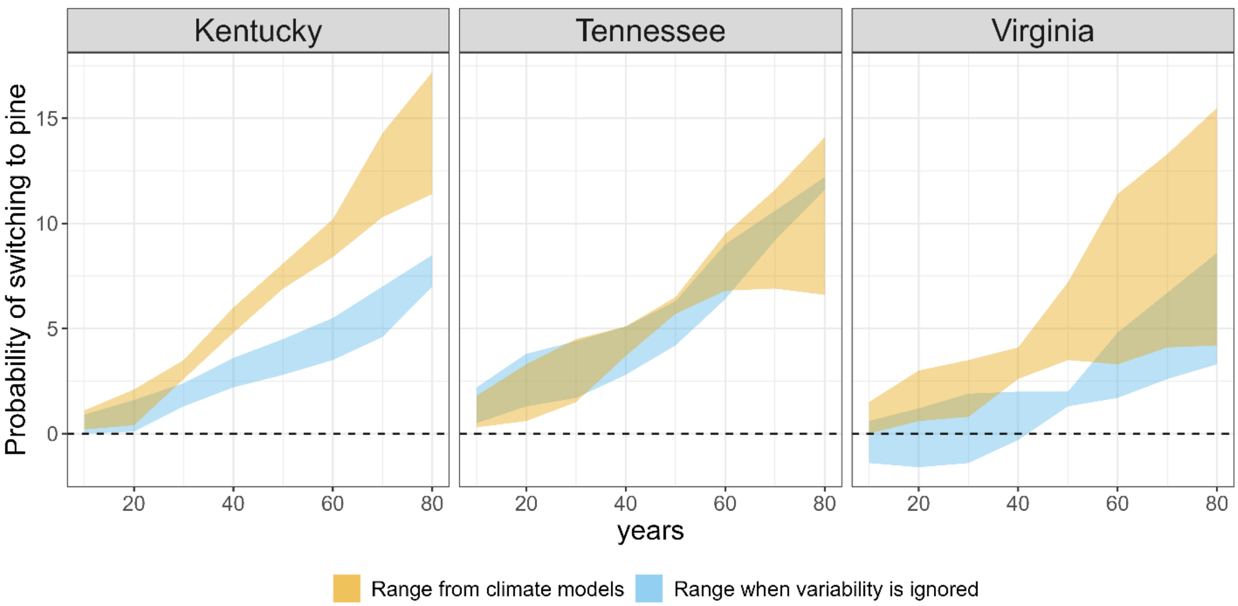

Figure A2.4 "High climate" plots: The orange (blue) band shows the range of adaptation paths generated by the range of projected climate across three climate models for the bio-economic simulation that includes weather variability (ignores weather variability).

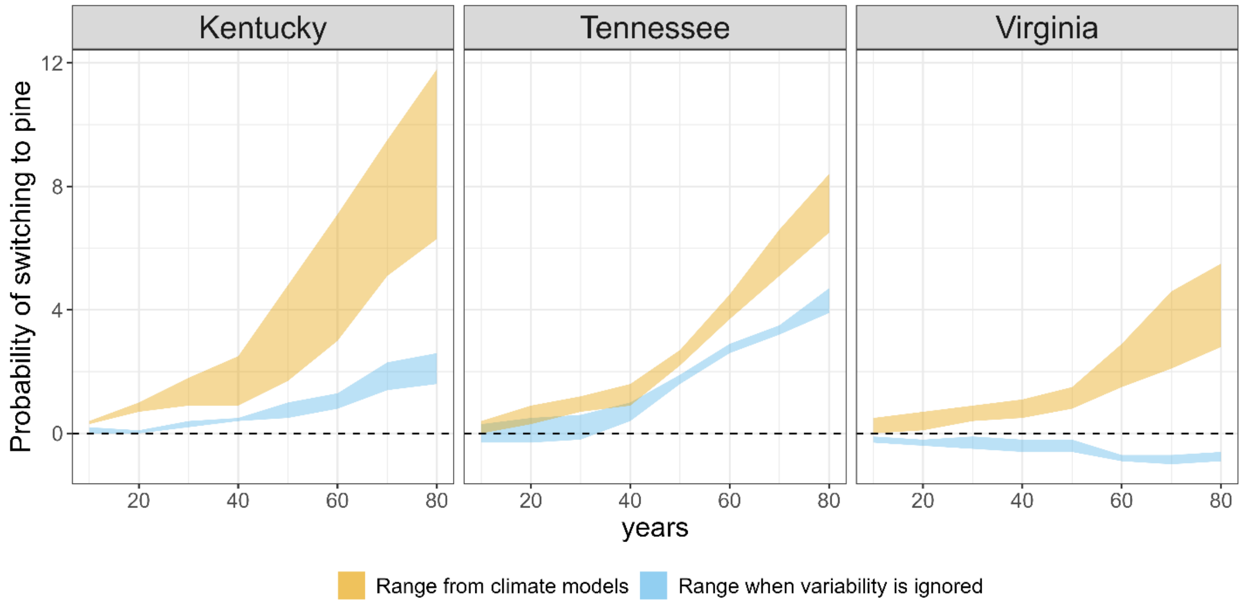

Figure A2.5 "Low climate" plots: The orange (blue) band shows the range of adaptation paths generated by the range of projected climate across three climate models for the bio-economic simulation that includes weather variability (ignores weather variability).

A3: Tables

Table A1: Planting model choice group definitions

Forest Group Name	Proportion of harvested plots that were artificially regenerated[1]	Choice group assignment
White / red / jack pine group	66.7%	Managed Pine
Longleaf / slash pine group	86.5%	Managed Pine
Loblolly / shortleaf pine group	79.8%	Managed Pine
Other softwoods group[2]	16.7%	Natural Hardwood
Oak / pine group	60.8%	Managed Pine
Oak / hickory group	22.4%	Natural Hardwood
Oak / gum / cypress group	21.6%	Natural Hardwood
Elm / ash / cottonwood group	20.3%	Natural Hardwood
Maple / beech / birch group	0.0%	Natural Hardwood
Other hardwoods group[3]	17.2%	Natural Hardwood

[1] To do this categorization, we take all observations that have been planted and determine the proportion of plots in each forest group that were artificially regenerated (as opposed to naturally regenerated). Forest groups with more than 50 percent of planted plots that were artificially regenerated are categorized as “managed pine” while those with less than 50 percent of plots artificially regenerated are categorized as “natural hardwood”. Results of this categorization can be found in the supplementary material (Table A1).
[2] The ‘Other softwoods’ classification includes the following forest groups: Spruce-Fir, other eastern softwoods, Pinyon-Juniper, and exotic softwoods.
[3] The ‘Other hardwoods’ classification includes the following forest groups: Aspen-Birch, other hardwoods, tropical hardwoods, and exotic hardwoods.

Table A2: List of data used and sources

Variable	Description	Units and scaling	Source
	Data used in estimation		
Clear Cut	1 if clear-cut; 0 if not	binary	FIA
Disturbed	1 if plot is disturbed and experienced negative growth; 0 if not	binary	FIA
mgd_pine	1 if a managed pine species is planted; 0 if not	binary	FIA
hardwood	1 if a hardwood species is planted; 0 if not	binary	FIA
site class	Measure of a plot's quality on a scale from 1 (highest quality) to 7 (lowest quality)	categorical	FIA
Elevation	Elevation	Ft (1000s)	FIA
Private	1 if land is privately owned; 0 if not	binary	FIA
State dummy	Binary variables indicating the plot's state	binary	FIA
Stand volume	Per acre volume calculated by multiplying the plot's measured trees by their trees/acre expansion factor (TPA) and summed for the plot	MBF/acre	FIA
Stand growth	Per acre volume growth calculated by multiplying each tree's recorded annual growth by their TPA and summed for the plot	MBF/acre/ year	FIA
Stand Age	Age of the stand at time of FIA measurement	Years	FIA
Clear Cut Revenue	Timber price multiplied by stand volume	\$1000/acre	FIA, Mihiar and Lewis 2021
No-cut benefit	Timber price multiplied by stand growth	\$1000/acre	FIA, Mihiar and Lewis 2021
Net Returns	Annualized net returns per acre	\$10/acre/year	Mihiar and Lewis 2021
Wtmax	Average maximum daily temperature Dec.-Feb.	Degrees Celcius/10	PRISM
Annual precip	Mean annual precipitation	mm/1000	PRISM
Days<0	Average number of days < 0°C annually calculated over previous 20 years	Count/10	PRISM
Short term Days<0	Average number of days < 0°C annually calculated over previous 5 years	Count/10	PRISM
Mean(temp)	Mean annual temperature	Degrees Celcius/100	PRISM
ngprecip	Average total precip from Dec.-Feb.	mm/1000	PRISM
	Additional data used in simulation		
Projected wtmax	Average maximum daily temperature Dec.-Feb calculated over the previous 20 years.	Degrees Celcius/10	MACA
Projected Days<0	Average annual days<0°C calculated over previous 20 years	Count/10	MACA
Projected short-term Days<0	Average annual days<0°C calculated over previous 5 years	Count/10	MACA

Projected annual precip	Mean annual precipitation calculated over the previous 20 years.	meters	MACA
Projected mean(temp)	Mean annual calculated over the previous 20 years.	Degrees Celcius/100	MACA
Projected ngprecip	Average total precip from Dec.-Feb calculated over the previous 20 years.	meters	MACA

Acronyms found in the Units and Source column are as follows: Forest Inventory and Analysis (FIA), Parameter-elevation Regressions on Independent Slopes Model (PRISM), and Multivariate Adaptive Constructed Analogs (MACA)

Table A3: Parameter estimates for the full nested logit model

Natural Disturbance Model (disturbed = 1, not disturbed = 0)		
	(1) wv = Days < 0°C	(2) No wv
Constant	-7.579***	-5.181***
	(1.548)	(1.164)
$\overline{tmean}$	25.064***	13.329*
	(7.583)	(6.090)
$\overline{ngprecip}$	-1.360	-2.113
	(1.224)	(1.139)
Short-term Days<0	0.192	
	(0.113)	
Pine	-1.059***	-0.723***
	(0.146)	(0.106)
Elevation	0.237	0.262*
	(0.130)	(0.123)
Private ownership	-0.962***	-0.970***
	(0.105)	(0.105)
Pine*Short-term Days<0	0.290***	
	(0.077)	
Fixed effects	Yes - state	Yes - state
Pseudo R^2_{McF}	0.037	0.034
Observations: 58,466		

Planting Model (plant pines = 1, plant hardwoods = 0)		
	(2) wv = Days < 0°C	(1) No wv
Constant	0.206	-2.334***
	(0.820)	(0.573)
$\overline{wtmax}$	-0.879	0.763*
	(0.499)	(0.324)
$\overline{Precip}$	1.602***	1.347***
	(0.308)	(0.302)
Net Returns	-0.015	-0.116
	(0.310)	(0.300)
Net Returns*$\overline{wtmax}$	-0.021	0.095
	(0.236)	(0.229)
Site Class	-0.143**	-0.142**
	(0.045)	(0.044)
Days<0	-0.662***	
	(0.157)	
Fixed Effects	No	No
Pseudo R^2_{McF}	0.028	0.024
Observations: 3,133		

Table A4 (continued)		
	Harvest Model (clear-cut = 1, no clear-cut = 0)	
	(1) wv = days < 0°C	(2)
Clear cut constant	-4.627***	-4.533***
	(0.070)	(0.072)
Clear cut revenue	0.053***	0.045***
	(0.008)	(0.008)
No cut benefit	-4.178***	-4.284***
	(0.298)	(0.299)
No cut benefit ^2	4.513***	4.566***
	(0.526)	(0.525)
Planting IV	2.229***	2.148***
	(0.088)	(0.093)
Disturbance IV	4.298	10.895**
	(3.109)	(3.419)
Fixed Effects	No	No
Pseudo R^2_{McF}	0.221	0.204
Observations: 61,599		

Table A4: Growth Model Estimates

	Growth Model (y = Δvolume (mbf/acre/year))
Constant	-0.4846***
	(0.1271)
$\overline{tmean}$	0.0152*
	(0.0062)
$\overline{ngprecip}$	0.0006***
	(0.0001)
Short-term Days<0	0.00674***
	(0.0009)
Pine	0.4346***
	(0.0112)
Elevation	-0.000049***
	(0.000011)
Private ownership	0.1389***
	(0.0107)
Pine*Short-term Days<0	-0.0100***
	(0.0007)
Fixed effects	Yes - state
R^2	0.052
Observations: 58,466	

Significance level: ***0.10%, **1%, *5

Table A5: Disturbance model comparisons of short-term vs long-term weather variability

Natural Disturbance Model (disturbed = 1, not disturbed = 0)		
	(1) wv = short-term Days < 0°C	(2) Wv=long-term Days<0°C
Constant	-7.579***	-5.183**
	(1.548)	(1.629)
$\overline{wtmean}$	25.064***	14.459
	(7.583)	(7.868)
$\overline{ngprecip}$	-1.360	-2.399
	(1.224)	(1.258)
Days<0	0.192	-0.082
	(0.113)	(0.139)
Pine	-1.059***	-1.084***
	(0.146)	(0.148)
Elevation	0.237	0.331*
	(0.130)	(0.134)
Private ownership	-0.962***	-0.968***
	(0.105)	(0.105)
Pine* Days<0	0.290***	0.323***
	(0.077)	(0.086)
Fixed effects	Yes - state	Yes - state
Pseudo R^2_{McF}	0.037	0.0361
Observations: 58,466		

Significance level: ***0.10%, **1%, *5

Table A6: Alternative planting model specifications.

	Planting Model (plant pines = 1, plant hardwoods = 0)		
	(1) wv = long-term Days < 0°C	(2) wv = short-term Days<0°C	(3) Fixed Effects wv = long-term days<0°C
Constant	0.206	-0.488	-0.259
	(0.820)	(0.769)	(0.903)
$\overline{wtmax}$	-0.879	-0.391	-0.736
	(0.499)	(0.456)	(0.545)
$\overline{Precip}$	1.602***	1.533***	1.754***
	(0.308)	(0.307)	(0.314)
Net Returns	-0.015	0.010	0.071
	(0.310)	(0.308)	(0.335)
Net Returns*$\overline{wtmax}$	-0.021	-0.044	-0.056
	(0.236)	(0.236)	(0.252)
Site Class	-0.143**	-0.148***	-0.151***
	(0.045)	(0.045)	(0.045)
Days<0	-0.662***	-0.450***	-0.436*
	(0.157)	(0.127)	(0.146)
Fixed Effects	No	No	Yes - Ecoregion
Pseudo R^2_{McF}	0.028	0.027	0.030
Observations: 3,133			

Significance level: ***0.10%, **1%, *5%,

Table A7: Current and future climate projections of simulated sample plots

	Current Climate (PRISM)					Projected 2099 Climate (RCP 8.5 MACA – CESM Model)			
Plot	**Days < 0**	$var(wtmin)$	$wtmean$ (°C)	$\overline{tmean}$ (°C)	$\overline{precip}$ (mm)	**Days < 0**	$wtmean$ (°C)	$\overline{tmean}$ (°C)	$\overline{precip}$ (mm)
KY mean climate	35.67	40.58	7.56	13.10	1227.4	12.7	11.38	18.67	1408.9
KY low climate	44.73	36.07	5.93	12.74	1065.78	15.85	9.85	18.22	1312.31
KY high climate	25.87	37.47	8.90	14.74	1352.93	7.80	12.40	20.36	1510.40
TN mean climate	23.07	37.68	9.35	14.49	1358.6	6.30	13.85	20.13	1579.3
TN low climate	43.73	32.67	7.21	11.34	1159.83	19.00	11.09	16.49	1375.03
TN high climate	15.21	35.10	10.93	15.33	1549.96	6.15	14.22	20.59	1648.11
VA mean climate	26.53	24.98	8.56	13.31	1128.73	8.10	12.53	19.10	1279.30
VA low climate	47.73	28.70	5.31	10.12	995.62	17.85	10.61	17.09	1149.90
VA high climate	12.47	26.38	11.60	15.61	1288.21	1.80	15.05	20.79	1303.06

A4: References

Mihiar, Christopher, and David J Lewis. 2021. Climate, adaptation, and the value of forestland: A national Ricardian analysis of the United States. Land Economics: 011620.