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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 withinregion 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 8.5%, 5.4% and 2.1% (10.1%, 7.9%, and 4.4%) 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 4.6%, 1.0% and 1.2% (2.0%, 4.3%, and 0.6%) 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 Virginia. 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 and Figures

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





Effect of a 1-day increase in *days<0* on the odds of planting pines

Figure A1 presents the estimated odds ratio and 95% confidence interval of planting pines that results from a 1-day increase in *days*<0. *The estimates presented are from our main planting model presented in the main text (right hand side) and from our planting model that is estimated* using a double-selection Lasso linear regression model (left hand side), which takes a machine learning approach to selecting the climate covariates. *Both models estimate that a 1-day increase in* days < 0 decreases the odds of planting pine by a factor of about 0.94, demonstrating the robustness of the logit estimates from our main planting model.

Table A1: Planting model choice group definitions

	Proportion of		
	harvested plots that		
	were artificially	Choice group	
Forest Group Name	regenerated ¹	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.

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 DecFeb. calculated over previous 20 years	Degrees Celcius/10	PRISM	
Annual precip	Mean annual precipitation calculated over previous 20 years	mm/1000	PRISM	
Days<0	Average number of days < 0°C annually calculated over previous 20 years	Count/10	PRISM	
Short term Davs<0	Average number of days < 0°C annually calculated over previous 5 years	Count/10	PRISM	
Mean(temp)	Mean annual temperature calculated over previous 5 years	Degrees Celcius/100	PRISM	
wprecip	Average total precip from DecFeb. calculated over previous 5 years	mm/1000	PRISM	
	Additional data used in simulation			
Projected wtmax	Average maximum daily temperature DecFeb 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	

Table A2: List of data used and sources

Table A2 (cont.)			
Projected short-	Average annual days<0°C calculated over previous 5	Count/10	MACA
term Days<0	years		
Projected	Mean annual precipitation calculated over the previous	meters	MACA
annual precip	5 years.		
Projected	Mean annual calculated over the previous 5 years.	Degrees	MACA
mean(temp)		Celcius/100	
Projected	Average total precip from DecFeb calculated over the	meters	MACA
ngprecip	previous 20 years.		

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)

Natural Disturbance Model			
(dist	$\frac{1}{1000} = 1$, not disturbed = (1)	(2)	
	$wv = Davs < 0^{\circ}C$	No wy	
Constant	-10 256***	-6.174***	
Constant	(1.560)	(1.122)	
tmean	35 011***	14.192*	
inicun	(7.883)	(5.861)	
nanrocin	0.698	0.038	
пуртестр	(0.927)	(0.896)	
Short-term Days<0	0.369**	(0.03.0)	
Short-term Days<0	(0.117)		
Dino	(0.11/)	-0 726***	
rme	$-1.000^{-1.0}$	(0.106)	
F1	(0.140)	0.218	
Elevation	0.182	(0.115)	
D	(0.118)	(0.113)	
Private ownership	-0.940***	-0.930****	
	(0.105)	(0.105)	
Pine*Short-term Days<0	0.298***		
	(0.077)		
Fixed effects	Yes - state	Yes - state	
Pseudo R ² _{McF}	0.038	0.034	
Observations: 58,466			
	Planting Model		
(plant p	nes = 1, plant hardwood	$ls = 0) \tag{1}$	
	(2) wy = Davs < 0°C	(1) No wv	
Constant	0.204	-2.334***	
	(0.820)	(0.573)	
wtmax	-0.878	0.763*	
w cillun	(0.499)	(0.324)	
Precin	1.602***	1.347***	
Γιστρ	(0.308)	(0.302)	
Net Returns	-0.015	-0.116	
	(0.310)	(0.300)	
Not Dotumo*	-0.021	0.005	
inei Keiums [*] wtmax	(0.236)	0.093	
	0.1/3**	(0.229)	
Site Class	-0.145	-0.142^{**}	
-	(0.043)	(0.044)	
Days<0	-U.662***		
	(0.156)		
Fixed Effects	No	No	
Pseudo R ² _{McF}	0.028	0.024	
Observations: 3,133			

Table A3: Parameter estimates for the full nested logit model

Table A3 (cont.)					
Harvest Model					
(cle	ear-cut = 1, no clear-cut =	= 0)			
	(1)	(2)			
	$wv = days < 0^{\circ}C$				
Clear cut constant	-4.601***	-4.522***			
	(0.070)	(0.072)			
Clear cut revenue	0.054***	0.046***			
	(0.008)	(0.008)			
No cut benefit	-4.123***	-4.251***			
	(0.298)	(0.298)			
No cut benefit ^2	4.476***	4.547***			
	(0.526)	(0.525)			
Planting IV	2.233***	2.158***			
C C	(0.088)	(0.093)			
Disturbance IV	7.645*	12.902***			
	(3.109)	(3.422)			
Fixed Effects	No	No			
Pseudo R ² _{McF}	0.218	0.202			
Observations: 61,599					
Significance level: ***	0.10%, **1%, *5				

יי ה וי אר וי				
$\begin{array}{l} \textbf{Binary Probit M}\\ (zero growth = 1 \ positive \end{array}$	Binary Probit Model $(\text{zero growth} = 1, \text{positive growth} = 0)$			
Constant	0.226			
Constant	(0.162)			
Age	-0.009***			
8-	(0.001)			
Age ²	2.32e-5**			
8	(7.77e-6)			
Elevation	-0.097***			
	(0.014)			
Private ownership	-0.313***			
_	(0.018)			
tmean	-1.186			
	(0.896)			
wprecip	-0.047			
	(9.21e-5)			
Short-term days<0	0.078***			
	(0.012)			
Pine	-0.175***			
	(0.019)			
Pine*short-term days<0	-0.024*			
	(0.011)			
	NI.			
Fixed Effects	NO No			
Clustered SE Decude \mathbf{P}^2	N0 0.016			
Observations ⁴	0.010			
Observations :	34,707			
Growth Mode	el			
$(y = \log(\Delta mbf/acre/$	(year))			
Constant	-0.362			
	(0.323)			
Age	0.022***			
	(0.001)			
Age ²	-1.55e-4***			
	(9.44e-6)			
Elevation	-0.040			
	(0.025)			
Private ownership	0.097***			
	(0.025)			
tmean	-8.157***			
	(1.644)			
wprecip	0.379*			
~ .	(0.191)			
Short-term days<0	-0.102***			
	(0.025)			
Pine	0.728***			
	(0.025)			
Pine*short-term days<0	-0.181***			
	(0.015)			

Table A4: Two-part Tobit growth model estimates

Table A4 (cont.)	
Fixed Effects	Yes - state
Clustered Se	Yes - county
\mathbb{R}^2	0.065
Observations ⁴ :	39,635
Significance level: ***0.10)%, **1%, *5

⁴ The binary probit model of the probability of zero growth is estimated with the 54,707 plots that experienced nonnegative growth. The growth model is estimated with the 39,635 plots that experienced positive growth.

Natural Disturbance Model					
(disturbed = 1, not disturbed = 0)					
	(1)	(2)			
	wv = short-term Days	wv=long-term			
	< 0°C	Days<0°C			
Constant	-10.256***	-7.678***			
	(1.560)	(1.5641)			
wtmean	35.011***	22.321**			
	(7.883)	(7.869)			
ngprecip	0.698	0.211			
	(0.927)	(0.935)			
Days<0	0.369**	0.106			
	(0.117)	(0.136)			
Pine	-1.060***	-1.080***			
	(0.146)	(0.147)			
Elevation	0.182	0.225			
	(0.118)	(0.121)			
Private ownership	-0.940***	-0.949***			
1	(0.105)	(0.105)			
Pine* Davs<0	0.298***	0.327***			
y	(0.077)	(0.086)			
Fixed effects	Yes - state	Yes - state			
Pseudo R ² _{McF}	0.037	0.0360			
Observations: 58,466					
Significance level: ***	*0.10%, **1%, *5				

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

Planting Model						
(plant pines = 1, plant hardwoods = 0)						
	(1) wv = long-term Days $< 0^{\circ}C$	(2) wv = short-term Days<0°C	(3) Fixed Effects wv = long-term days<0°C			
Constant	0.204	-0.488	-0.807			
	(0.820)	(0.769)	(0.850)			
wtmax	-0.878	-0.390	-0.378			
	(0.499)	(0.456)	(0.504)			
Precip	1.602***	1.533***	1.723***			
	(0.308)	(0.307)	(0.313)			
Net Returns	-0.015	0.010	0.087			
	(0.310)	(0.309)	(0.335)			
Net Returns* wtmax	-0.021	-0.044	-0.067			
	(0.236)	(0.236)	(0.252)			
Site Class	-0.143**	-0.148***	-0.154***			
	(0.045)	(0.045)	(0.045)			
Days<0	-0.662***	-0.450***	-0.264			
-	(0.156)	(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 A6: Alternative planting model specifications.

Current Climate (PRISM)			Projected 2099 Climate (RCP 8.5 MACA – CESM Model)					
Plot	Days < 0 (20yr mean)	wtmean (°C)	tmean (°C)	mecip (mm)	Days < 0 (20yr mean)	wtmean (°C)	tmean (°C)	mecip (mm)
KY mean								
climate	35.67	7.56	13.10	1227.4	12.7	11.38	19.35	1408.9
KY low								
climate	44.73	5.93	12.74	1065.78	15.85	9.85	18.93	1312.31
KY high								
climate	25.87	8.90	14.74	1352.93	7.80	12.40	21.07	1510.40
TN mean								
climate	23.07	9.35	14.49	1358.6	6.30	13.85	20.77	1579.3
TN low								
climate	43.73	7.21	11.34	1159.83	19.00	11.09	17.17	1375.03
TN high								
climate	15.21	10.93	15.33	1549.96	6.15	14.22	21.25	1648.11
VA mean								
climate	26.53	8.56	13.31	1128.73	8.10	12.53	19.88	1279.30
VA low								
climate	47.73	5.31	10.12	995.62	17.85	10.61	17.86	1149.90
VA high								
climate	12.47	11.60	15.61	1288.21	1.80	15.05	21.49	1303.06

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

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.