Adapting to the Weather: Lessons from U.S. History[*]

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Abstract

An important unknown in understanding the impact of climate change is the scope for adaptation, a long-term process that requires observations on historical time scales. We consider the impact of weather across much of US history on various measures of productivity. Using cross-sectional and panel methods, we document economically and statistically significant responses of income to weather. We find particularly strong effects of hotter and wetter weather early in US history, but these effects are almost completely attenuated in recent decades. We evaluate several possible channels through which these adaptations took place. We contrast our results to the existing literature that makes inferences from shorter time horizons.

Keywords: climate change, adaptation, hedonics, farm value, cohort effects

[*] Chart pack prepared for ASSA 2010 Meetings in Atlanta. Preliminary results. Please do not cite without permission.

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Table 1. Fixed-Effects Estimates of Difference in Climatic Impacts on County Farm Value per Acre between the Late 19th and Late 20th Centuries

Dependent variable: ln(county average farmland value per acre)

Key Control Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: All Counties								
Temperature(*T*)**D*19	-0.0800***	-0.0607***	-0.0466***				-0.0512***	-0.0521***	-0.0520***
	(0.0021)	(0.0060)	(0.0063)				(0.0026)	(0.0058)	(0.0063)
Precipitation(*P*)**D*19				-0.0374***	-0.0269***	-0.0164***	-0.0170***	-0.0210***	-0.0114***
				(0.0013)	(0.0024)	(0.0029)	(0.0016)	(0.0023)	(0.0029)
$(T-\mu_T)*(P-\mu_P)*D19$							-0.0024***	-0.0020***	-0.0020***
							(0.0002)	(0.0003)	(0.0003)
	Panel B: South Region								
Temperature(*T*)**D*19	-0.0757***	-0.1052***	-0.0967***				-0.0824***	-0.0820***	-0.1049***
	(0.0050)	(0.0095)	(0.0102)				(0.0076)	(0.0114)	(0.0100)
Precipitation(*P*)**D*19				-0.0228***	-0.0431***	-0.0283***	-0.0189***	-0.0189***	-0.0425***
				(0.0030)	(0.0035)	(0.0041)	(0.0051)	(0.0049)	(0.0059)
$(T-\mu_T)*(P-\mu_P)*D19$							0.0007	-0.0026***	0.0016***
							(0.0007)	(0.0007)	(0.0006)
	Panel C: Non-South Region								
Temperature(*T*)**D*19	-0.0182***	-0.0431***	-0.0168**				0.0011	-0.0185**	-0.0183***
	(0.0045)	(0.0082)	(0.0073)				(0.0047)	(0.0088)	(0.0078)
Precipitation(*P*)**D*19				-0.0069***	-0.0185***	-0.0090**	-0.0102***	-0.0157***	-0.0094***
				(0.0019)	(0.0031)	(0.0038)	(0.0030)	(0.0037)	(0.0045)
$(T-\mu_T)*(P-\mu_P)*D19$							-0.0005	0.0000	-0.0007***
							(0.0004)	(0.0005)	(0.0006)
Standard Regressors	NO	YES	YES	NO	YES	YES	NO	YES	YES
Year FE	YES	NO	NO	YES	NO	NO	YES	NO	NO
State by Year FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
County FE	NO	NO	YES	NO	NO	YES	NO	NO	YES

Notes: We compared the counties in the census years of 1870, 1880, and 1890 with those in the census years of 1970, 1980, and 1990 (reference group). For climate variables, we used the decade (10 years before each census year) average of annual mean temperature (*T*) and that of annual accumulated precipitation (*P*). μ_T and μ_P denote the mean value of temperature and precipitation across counties and years, respectively. *D*19 denotes the dummy variable indicating the census years in the 19th century (i.e. 1870, 1880 or 1890). The standard regressors include (1) the climate variables without century dummy, (2) the number of male farmers per farmland acre, (3) the ratio of white population out of county population, (4) the ratio of farmland out of total available county area, and (5) the interactions of (2)-(4) with *D*19. Standard errors, clustered on county, are reported in parentheses. Single asterisk denotes statistical significance at the 90% level of confidence, double 95%, triple 99%.

Table 2. Differential Weather Sensitivity by Malaria Ecology

Dependent variable: ln(county average farmland value per acre)

Key Control Variables	Basic (1)	Malaria (2)
Temperature(*T*)**D*19	-0.0520*** (0.0063)	-0.0284*** (0.0091)
Precipitation(*P*)**D*19	-0.0114*** (0.0029)	0.0029 (0.0062)
$(T-\mu_T)*(P-\mu_P)*D19$	-0.0020*** (0.0003)	-0.0007 (0.0004)
*T*Malaria*D*19		-0.1626*** (0.0377)
*P*Malaria*D*19		-0.0808*** (0.0272)

Notes: This table reports the results of state by year & county fixed effects model done for all the counties. The setup is the same to that of Table 1. 'Basic' regression is adopted from the model (9) of Table 1. 'Malaria' denotes the estimated county malaria ecology index. In model (2), we also controlled fro (1) the interactions between climate and malaria ecology without century dummy and malaria and (2) the malaria ecology with century dummy. The malaria ecology variable itself was dropped by county fixed effects model.

Table 3. Explaining Differential Weather Sensitivity: Pre-Existing Agricultural Factors

Dependent variable: ln(county average farmland value per acre)

Key Control Variables	Basic (1)	Malaria (2)	% Cropland (3)	% Improved Farmland (4)	% Drained Areas c. 1930 (5)	% Irrigated Areas c. 1890 (6)	Crop HHI (7)	% Share-croppers (8)	% Tenants (9)	ln(Fertilizer Cost per Acre) (10)	Pellagra Index (11)
Temperature(*T*)**D*19	-0.0520*** (0.0063)	-0.0284*** (0.0091)	-0.0141 (0.0090)	-0.0273*** (0.0089)	-0.0273*** (0.0089)	-0.0285*** (0.0091)	-0.0222** (0.0091)	-0.0182* (0.0098)	-0.0258*** (0.0099)	-0.0299*** (0.0100)	-0.0213** (0.0101)
Precipitation(*P*)**D*19	-0.0114*** (0.0029)	0.0029 (0.0062)	0.0054 (0.0059)	0.0069 (0.0063)	0.0065 (0.0064)	0.0035 (0.0063)	0.0073 (0.0063)	0.0007 (0.0066)	0.0072 (0.0068)	-0.0049 (0.0071)	-0.0045 (0.0067)
$(T-\mu_T)*(P-\mu_P)*D19$	-0.0020*** (0.0003)	-0.0007 (0.0004)	-0.0003 (0.0004)	-0.0001 (0.0004)	-0.0005 (0.0004)	-0.0004 (0.0005)	-0.0002 (0.0004)	-0.0008* (0.0004)	-0.0005 (0.0004)	-0.0013** (0.0005)	-0.0006 (0.0004)
*T***Malaria***D*19		-0.1626*** (0.0377)	-0.0697** (0.0345)	-0.0688** (0.0350)	-0.1700*** (0.0375)	-0.1671*** (0.0375)	-0.1254*** (0.0365)	-0.1785*** (0.0404)	-0.1376*** (0.0402)	-0.1347*** (0.0371)	-0.1943*** (0.0409)
*P***Malaria***D*19		-0.0808*** (0.0272)	-0.0896*** (0.0243)	-0.0707*** (0.0268)	-0.0816*** (0.0268)	-0.0807*** (0.0273)	-0.0922*** (0.0268)	-0.0745*** (0.0280)	-0.1031*** (0.0286)	-0.0541* (0.0297)	-0.0489* (0.0285)
$T*(Factor-\mu_F)*D19$			0.0885*** (0.0165)	-0.0028 (0.0123)	-0.0059 (0.0124)	0.1315*** (0.0486)	0.1752** (0.0749)	0.0695*** (0.0242)	0.0062 (0.0202)	0.0029* (0.0017)	0.0128 (0.0234)
$P*(Factor-\mu_F)*D19$			0.0462*** (0.0113)	0.0603*** (0.0075)	0.0410*** (0.0089)	0.0233 (0.0448)	0.2205*** (0.0486)	-0.0136 (0.0144)	0.0119 (0.0120)	-0.0024** (0.0010)	-0.0382*** (0.0140)

Notes: This table reports the results of state by year & county fixed effects model done for all the counties. The setup is the same to those of Tables 1 and 2. 'Basic' and 'Malaria' regressions are adopted from Table 2. 'Factor' means the value of agricultural factors denoted in the head of each column. μ_F is its average value. The detailed information of each agricultural factor is reported in the text. In models (3)-(11), we also controlled for (1) the interactions between climate and factor without century dummy and malaria, (2) factor with century dummy, and (3) factor without century dummy.

Table 4. Explaining Differential Weather Sensitivity: Crop Selection

Dependent variable: ln(county average farmland value per acre)

Key Control Variables	Basic (1)	Malaria (2)	Cotton (3)	Rice (4)	Wheat (5)	Corn (6)	Barley (7)	Oats (8)
Temperature(*T*)**D*19	-0.0520*** (0.0063)	-0.0286*** (0.0093)	-0.0072 (0.0104)	-0.0348*** (0.0090)	-0.0332*** (0.0092)	-0.0155 (0.0108)	-0.0296*** (0.0092)	-0.0240*** (0.0093)
Precipitation(*P*)**D*19	-0.0114*** (0.0029)	0.0016 (0.0064)	0.0020 (0.0069)	-0.0004 (0.0063)	0.0050 (0.0064)	-0.0020 (0.0078)	0.0048 (0.0063)	0.0019 (0.0064)
$(T-\mu_T)*(P-\mu_P)*D19$	-0.0020*** (0.0003)	-0.0008* (0.0005)	-0.0005 (0.0004)	-0.0010** (0.0004)	-0.0005 (0.0004)	-0.0009** (0.0004)	-0.0007 (0.0005)	-0.0008* (0.0004)
*T***Malaria***D*19		-0.1596*** (0.0382)	-0.2045*** (0.0428)	-0.1534*** (0.0375)	-0.1107*** (0.0374)	-0.1297*** (0.0399)	-0.1598*** (0.0374)	-0.1520*** (0.0371)
*P***Malaria***D*19		-0.0785*** (0.0281)	-0.0841*** (0.0294)	-0.0618** (0.0273)	-0.0765*** (0.0270)	-0.0729** (0.0289)	-0.0858*** (0.0271)	-0.0753*** (0.0274)
$T*(Factor-\mu_F)*D19$			0.2159* (0.1127)	1.5995 (2.3045)	0.0836** (0.0384)	0.2122*** (0.0622)	0.2060 (0.2860)	0.3000** (0.1310)
$P*(Factor-\mu_F)*D19$			-0.0449 (0.0442)	-0.1793 (0.3382)	0.1647*** (0.0247)	0.0096 (0.0391)	0.3113*** (0.1176)	-0.0020 (0.0662)

Notes: This table reports the results of state by year & county fixed effects model done for all the counties. The setup is the same to those of Tables 1 and 2. 'Basic' and 'Malaria' regressions are adopted from Table 2. 'Crop' means the percentage of crop (as denoted in the head of each column) out of total available crop land. μ is its average value.

Table 5. Explaining Differential Weather Sensitivity: Change in Agricultural Factors

Dependent variable: ln(county average farmland value per acre)

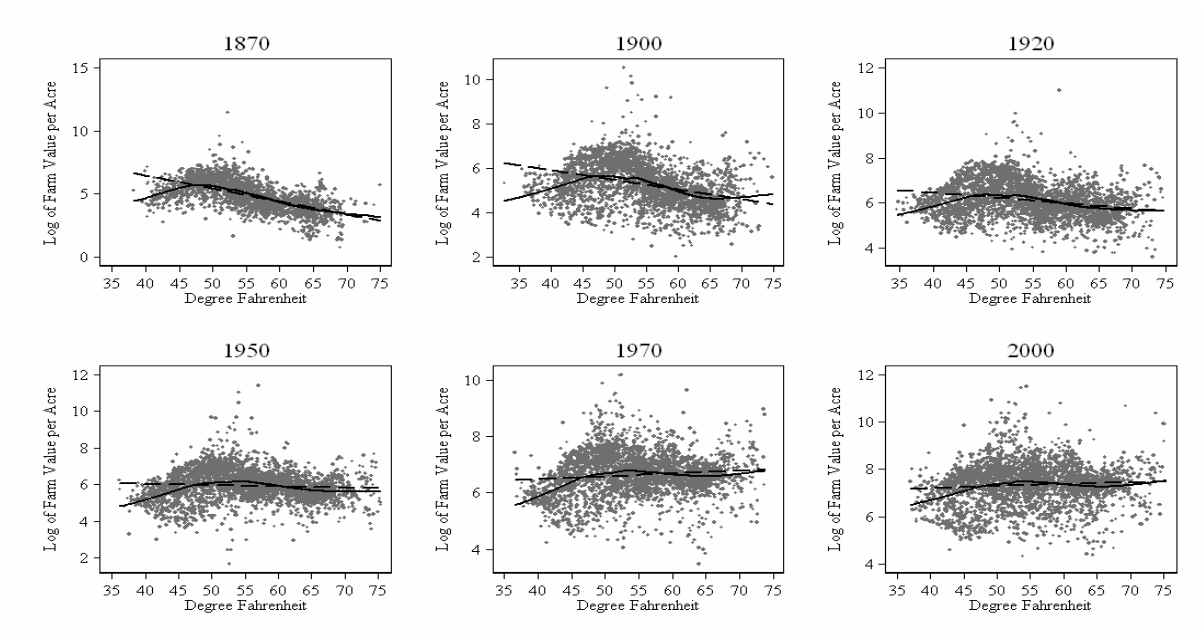
Key Control Variables	Basis (1)	Malaria (2)	Δ % Cropland (3)	Δ % Improved Farmland (4)	Δ Crop HHI (7)	Δ % Cotton Acres (8)	Δ % Tenants (9)	Δ Fertilizer Cost (10)
Temperature(*T*)**D*19	-0.0520*** (0.0063)	-0.0284*** (0.0091)	-0.0348*** (0.0082)	-0.0275*** (0.0088)	-0.0279*** (0.0088)	-0.0164* (0.0097)	-0.0249*** (0.0091)	-0.0275*** (0.0092)
Precipitation(*P*)**D*19	-0.0114*** (0.0029)	0.0029 (0.0062)	0.0085* (0.0049)	0.0071 (0.0065)	0.0026 (0.0060)	-0.0021 (0.0066)	0.0037 (0.0066)	0.0022 (0.0065)
$(T-\mu_T)*(P-\mu_P)*D19$	-0.0020*** (0.0003)	-0.0007 (0.0004)	-0.0002 (0.0004)	-0.0002 (0.0005)	-0.0006 (0.0004)	-0.0010** (0.0004)	-0.0005 (0.0004)	-0.0007 (0.0004)
*T***Malaria***D*19		-0.1626*** (0.0377)	-0.1162*** (0.0334)	-0.1350*** (0.0350)	-0.1489*** (0.0360)	-0.1922*** (0.0398)	-0.1813*** (0.0383)	-0.1625*** (0.0380)
*P***Malaria***D*19		-0.0808*** (0.0272)	-0.0867*** (0.0223)	-0.0753*** (0.0272)	-0.0779*** (0.0261)	-0.0642** (0.0278)	-0.0831*** (0.0278)	-0.0783*** (0.0277)
$T*(Factor-\mu_F)*D19$			-0.0077 (0.0131)	0.0320** (0.0126)	-0.1795*** (0.0395)	-0.0460 (0.0909)	0.0007** (0.0003)	0.0241*** (0.0093)
$P*(Factor-\mu_F)*D19$			0.0242*** (0.0076)	-0.0288*** (0.0078)	-0.0391** (0.0197)	0.0709*** (0.0271)	0.0005** (0.0002)	-0.0146 (0.0099)

Notes: This table reports the results of state by year & county fixed effects model done for all the counties. The setup is the same to those of Tables 1-4. 'Basic' and 'Malaria' regressions are adopted from Table 2. 'ΔFactor' means the change of agricultural factors denoted in the head of each column. $\mu_{\Delta F}$ is its average value.

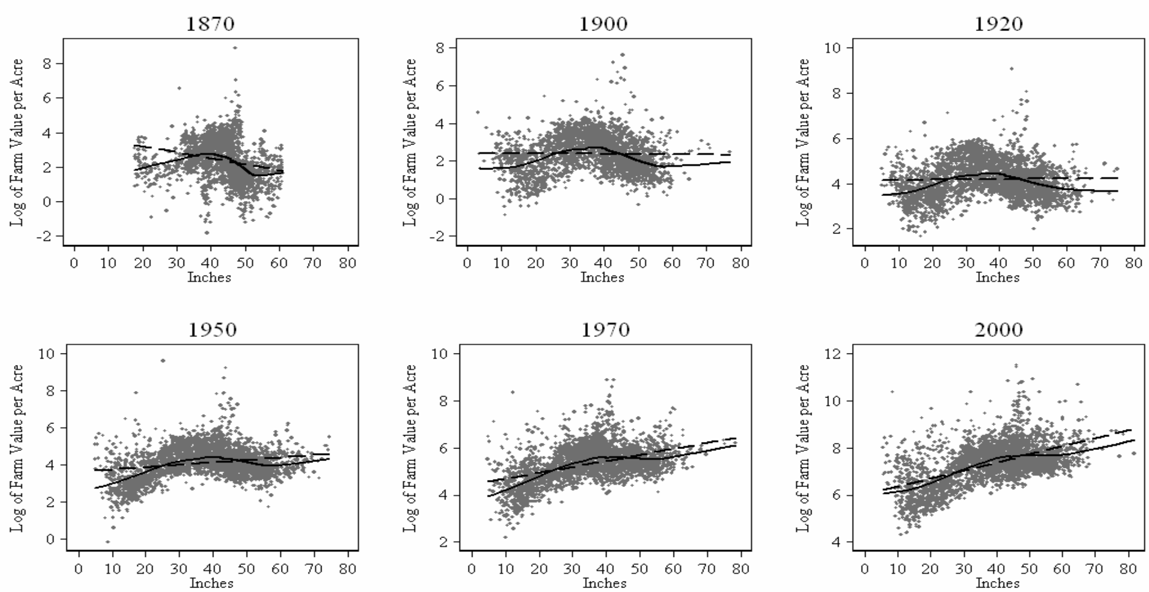
Figure 1. Scatter Plots: Log County Average Farm Value per Acre by Decadal Climate

(Solid Curve: Lowess Fits, Dashed Lines: Linear Fits)

Decade Average of County Annual Mean Temperature



Decade Average of County Annual Accumulated Precipitation



Note: Decade climate values are calculated by the 10-year average of annual weather records prior to each census year.

Figure 2. Scatter Plots: Log County Average Farmland Value per Acre by Decade Malaria Risk Index

(Solid Curve: Lowess Fits, Dashed Lines: Linear Fits)

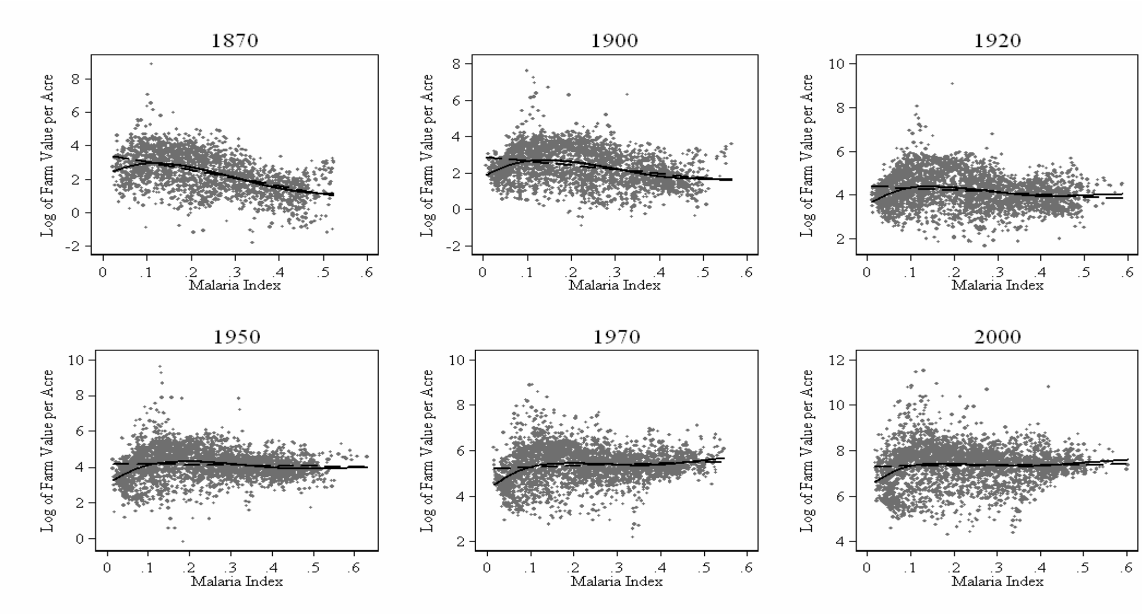
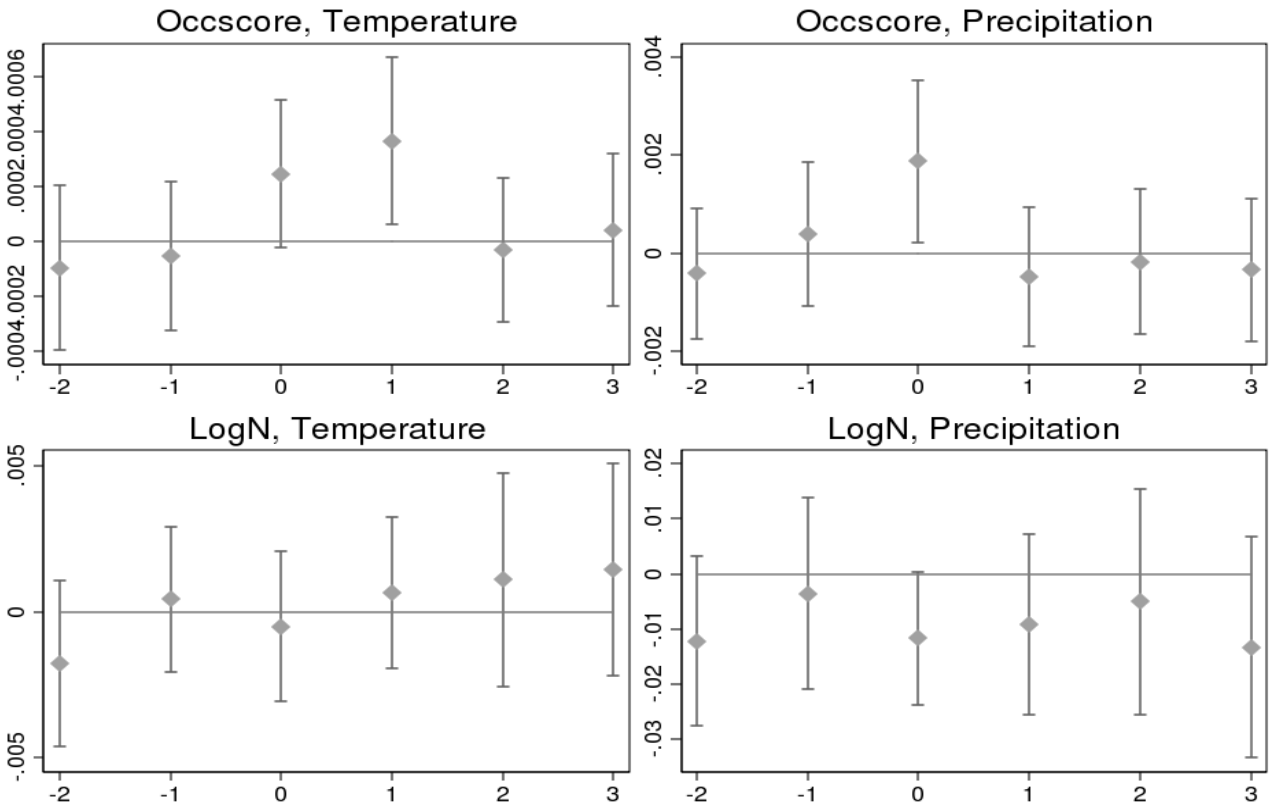
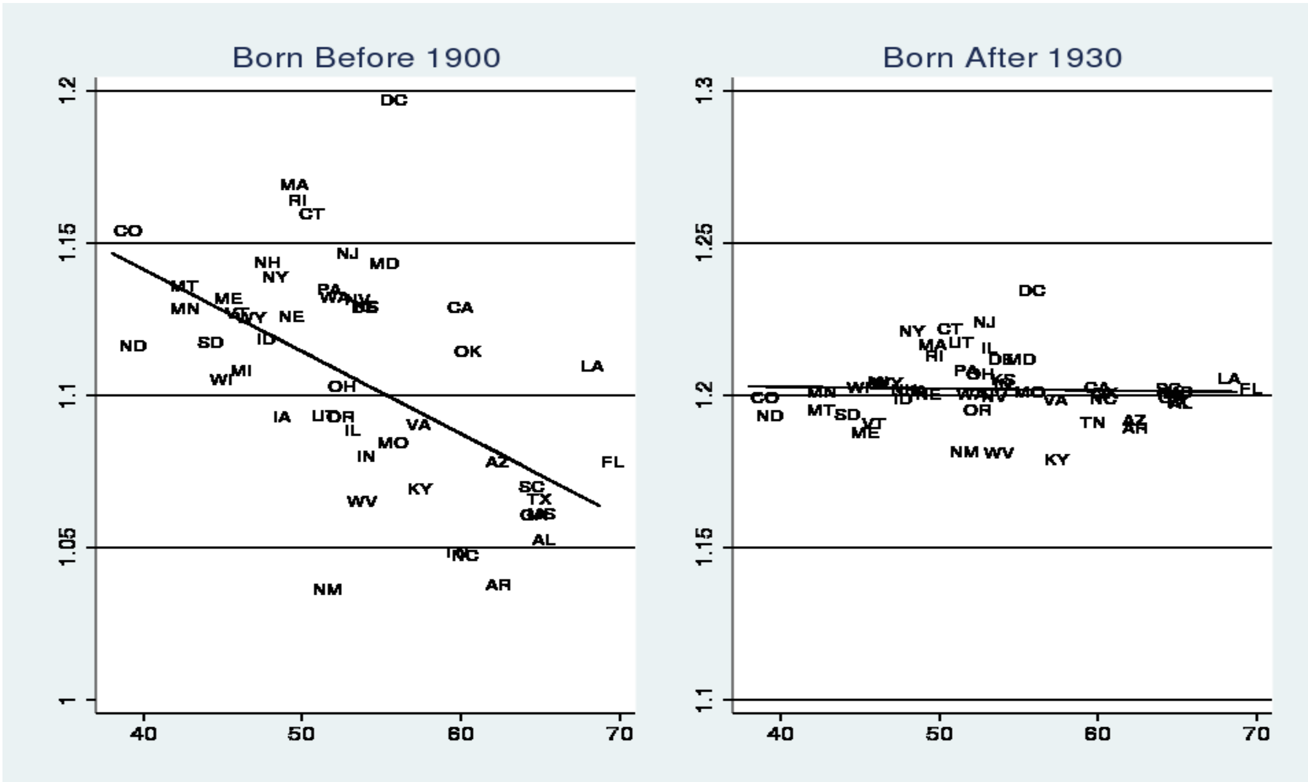


Figure 3. Effects of Short-Term Weather Fluctuations Early in Life



Note: This figure summarizes regressions of cohort outcomes on early-life weather conditions, per equation (3) in the text. A cohort is defined by year of birth and state of birth. Data on native adult males are drawn from U.S. censuses of 1880-1990, which span the years of birth 1825-1960. The outcome variables are, at the cohort level, the occupational income score and cell size, both transformed into natural logarithms. The *x* axis in each plot refers to the calendar year minus the year of birth. The *y* axis in each plot displays the estimated regression coefficient on the interaction of the indicated weather variable (temperature or precipitation) and a dummy for the calendar year minus year of birth. The error bars reflect 95% confidence intervals for each coefficient. The regressions also contain a 4-order trend in year of birth interacted with state-of-birth dummies, dummies for each cell of year of birth times census year, and dummies for each cell of state of birth times census year. The weather coefficients are estimated simultaneously in the same regression for each dependent variable. Sources and methods of data construction are described in the appendix.

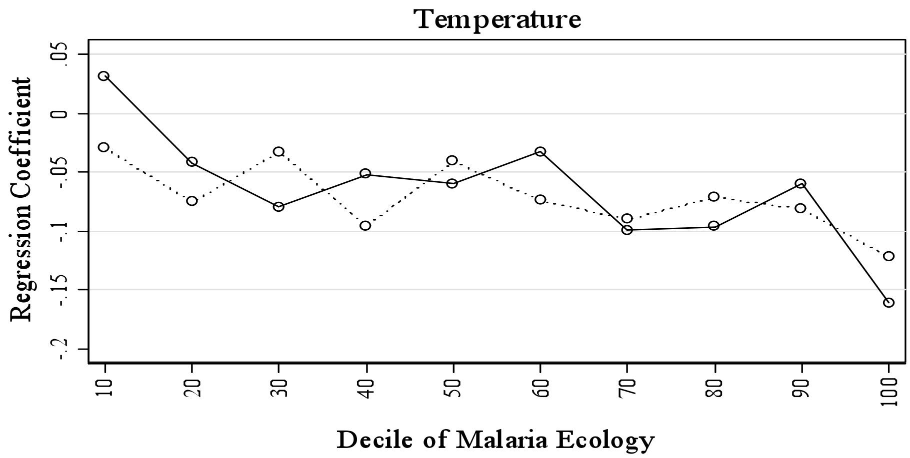
Figure 4. Adult Income and Average Temperature in State of Birth

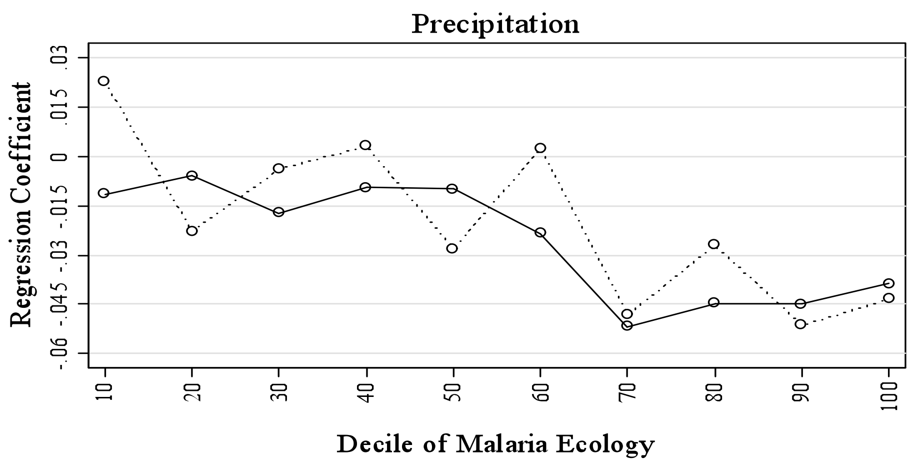


Note: This figure plots a proxy of adult income against the state-of-birth average temperature for earlier- and later-born cohorts in the U.S. A cohort is defined by year of birth and state of birth. Data on native adult males are drawn from U.S. censuses of 1880-1990, which span the years of birth 1825-1960. The outcome variable is the average occupational income score, transformed into natural logarithms. Cohorts are grouped into those born before 1900 (in the left-hand plot) and those born after 1930 (in the right-hand plot). The *x* axis in each plot is the state-of-birth average temperature. The *y* axis in each plot refers to the cohort group's average income score. The same scaling of the *x* and *y* axes is used for the two plots. State abbrevations are used to denote the position of each point. The solid line is the best-fit regression line between the points. Sources and methods of data construction are described in the appendix.

Figure 5. Difference in Climatic Impact on Farm Value between the Late 19th and Late 20th Centuries by Average Malaria Ecology Deciles

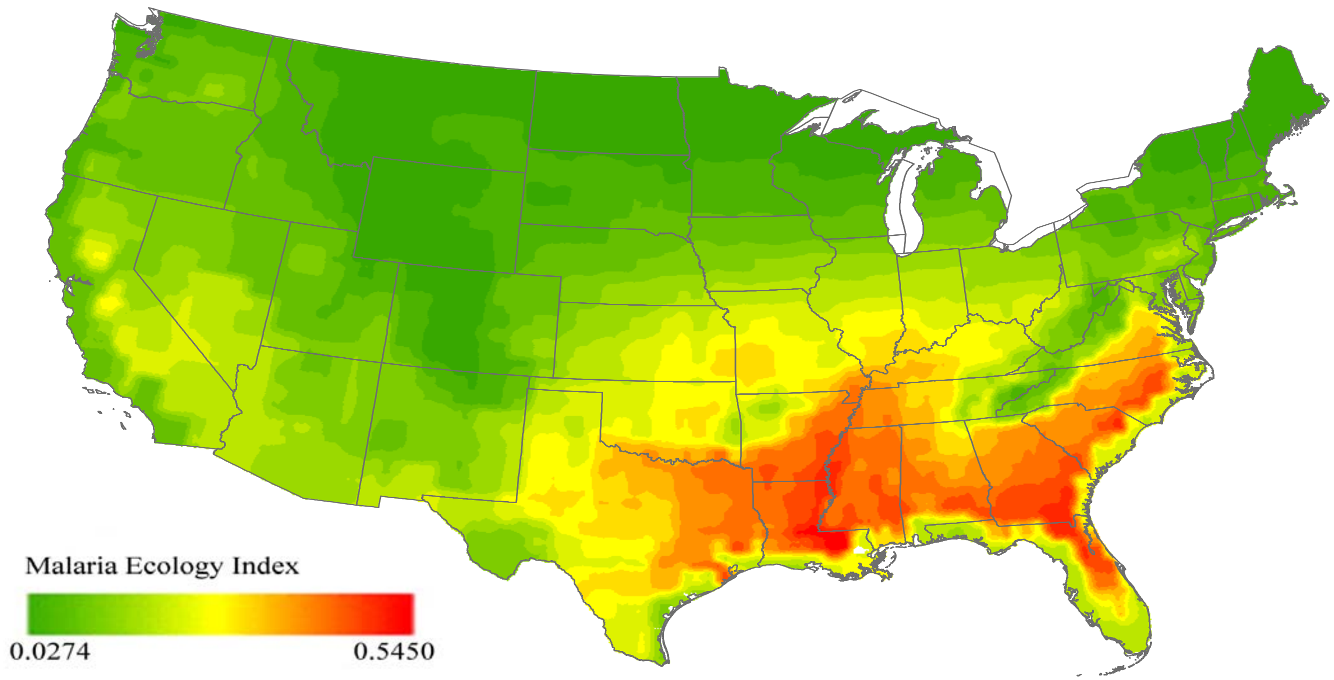
(Solid Line: State by Year FE, Dotted Line: State by Year & County FE)





Notes: In regression models (2), (3), (5), and (6) of Table 1, we estimated the difference of climate impacts on farm value between the late 19th and late 20th centuries by census regions (all, South, or non-South), using state by year FE or county FE models. Here we conducted the same regressions for the 10 county groups divided by average malaria ecology deciles. The above graphs show the difference of climatic impacts between the 19th and 20th centuries by malaria ecology (the regression coefficients of *Climate***D*19 in Table 1, where D19 is the dummy of years in the 19th century).

Figure A.1. U.S. Malaria Ecology Index in 1861-2000



Notes: This diagram shows the average of decade malaria ecology indexes in 1861-2000. More red (green) areas have a higher (lower) risk of contracting malarial fevers. Each decade's malaria ecology index is estimated by two main data sources: (1) the county-level environmental records on temperature, rainfall, and geographical features (standard deviation of elevation and dummy of ocean), and (2) the annual incidence of malarial fever found in the U.S. fort sickness reports between 1829 and 1874. We first estimated the correlation between forts' annual malaria incidence rates and those environmental factors around forts. Then, we imputed the risk index by plugging decade county-level environment variables into the above estimation result. More details of estimation procedure and its results are discussed in Hong, S.C. (2007), "The Burden of Early Exposure to Malaria in the United States, 1850-1860: Malnutrition and Immune Disorders." *The Journal of Economic History* 67(4): 1001-35.