EC1340 Topic #6

Climate damage III: The Little Ice Age

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Outline

The 'Little Ice Age' was a period of cold from about the late 1500's until about the early 1700's. This is exactly the variation in climate that we need to study the effects of climate change. We look at four studies that do exactly this.

1. Zhang et al. PNAS 2007
2. Oster, JEP 2004
3. Turner, AERPP 2012
4. Waldinger JPE 2022

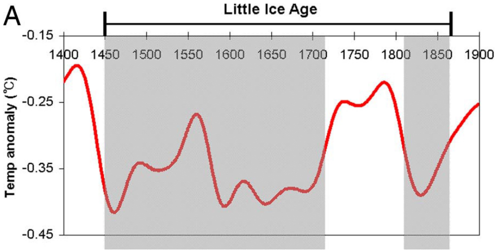
These studies use exactly the right variation, but do so in a much less developed world, and consider cooling not warming.

Zhang et al. PNAS 2007

Global climate change, war and population decline in recent human history

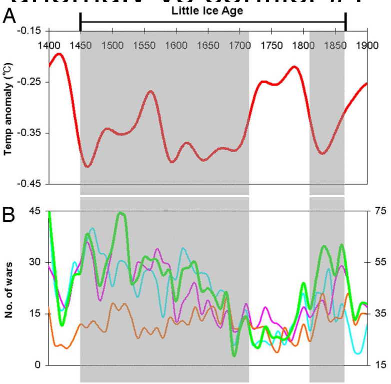
- This paper assembles long time series of data describing temperature, population, and conflict, and plots them next to each other.
- The paper really boils down to a series of figures.
- N.B.: This is a paper by anthropologists, and so it reads a little bit differently than an economics paper.

Temperature anomaly



- This is mean Northern Hemisphere (NH) temperature that has been put through a ‘filter’(i.e., moving average) to smooth it out.
- There is a clear cold period from about 1450 to 1720. Dates move around a little with different data sources.
- This was the pre-industrial period when urbanization rates in Europe increased slowly (from about 10%-12%) and productivity increased slowly (until about 1750).

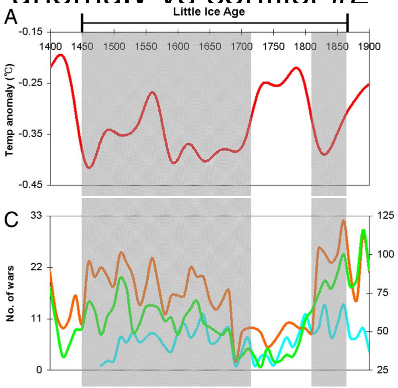
Temperature anomaly vs conflict #1



- Total NH wars (Green), Asia (Pink), Europe (Turquoise), Arid areas (Orange).
- More war in cold times, less in warm times. What is the mechanism?
- Why not make temperature series to match war series, e.g. European temperature?

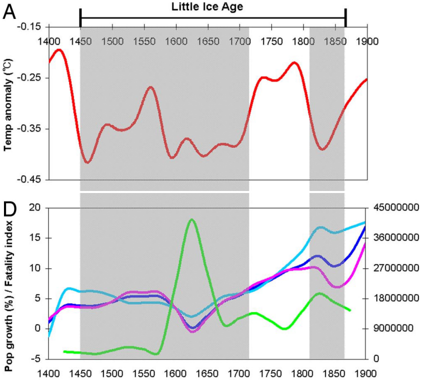
Zhang et al. PNAS 2007

Temperature anomaly vs conflict #2



- Total NH wars (Green), Asia (Pink), Europe (Turquoise), Arid areas (Orange).
- Different data source.
- Same pattern. More wars in cold times, less in warm times.
- Should this increase our confidence? (think measurement error).

Temperature anomaly vs population



- Pop Growth % Europe (Turquoise), Pink (Asia), NH (blue). NH 50 year fatality index.
- There is no obvious pattern here. What does this suggest about the mechanism behind the conflict result?

Conclusion, Zhang et al., PNAS 2007

- Suggestive evidence for a relationship between temperature and conflict.
- That temperature is not always defined over same geography as conflict is suspicious.
- There were other trends going on in the world during this time, too, e.g., economic growth, urbanization, the Colombian exchange.
- The data does not show the same pattern between climate and population growth. What would it show for population level? This makes the mechanism behind the conflicts unclear.

Oster, JEP 2004

Witchcraft, Weather and Economic Growth in Renaissance Europe

- Compare frequency of witch trials over the course of the little ice age in Europe.
- Why is this interesting? (1) Witch trials are bad and we want fewer of them. (2) We think witch trials are reflection of economic hardship.
- Issues: Same as Zhang et al. Is medieval European cooling informative about the costs of modern warming? There are other trends during this time.
- Also, it would be nice to know the relationship between witch trials and hardship a little more precisely.

Data

- Oster's data records witch trials in 11 European regions: Basel, Essex, Estonia, Finland, Eastern France, Geneva, England, Hungary.
- Data is by decade from 1520–1770. So, $k = 11, t = 1520 - 1770$. Some are missing, so $N = 170$ not $11 \times 25 = 275$.
- $k \sim$ regions, $t \sim$ decades.
- Let W_{kt} be # trials in region k decade t.

Measuring witch trials I

There are two econometric issues.

- Region specific propensity to try witches that may be correlated with mean climate.
- Some regions are much bigger than others and so tend to dominate regression results.

Response

- ‘de-mean’ the data. This is *almost* equivalent using a region fixed effect.
- normalize variance. This is almost equivalent to adding copies of small regions to the data set so they count have a bigger effect on the regression. This is called ‘re-weighting’. This will lead to trouble interpreting the results.
- Comment: non-standard solutions to these problems.

Measuring witch trials II

Let

$$\overline{W}_k = \frac{1}{25}\sum_{t=1}^{25} W_{kt}$$

$$SD(W_k) = \left[\frac{1}{25}\sum_{t=1}^{25}(W_{kt} - \overline{W}_k)^2\right]^{\frac{1}{2}}$$

Define

$$W_{kt}^* = \frac{W_{kt} - \overline{W}_k}{SD(W_k)}$$

This is the dependent variable measuring the incidence of witch trials.

Measuring witch trials III

W^*_{kt} has mean zero.

$$
\begin{aligned}
\frac{1}{25}\sum_{t=1}^{25} W^*_{kt} &= \frac{1}{25}\sum_{t=1}^{25}\frac{W_{kt}-\overline{W}_k}{SD(W_k)} \\
&= \frac{1}{25SD(W_k)}\sum_{t=1}^{25}\left[W_{kt}-\overline{W}_k\right] \\
&= \frac{1}{25SD(W_k)}\left[\sum_{t=1}^{25}W_{kt}-25\overline{W}_k\right] \\
&= \frac{1}{25SD(W_k)}25\left[\overline{W}_k-\overline{W}_k\right] \\
&= 0
\end{aligned}
$$

W^*_k is 'demeaned'.

Measuring witch trials IV

W_k^* has standard deviation 1 for each k.

$$
\begin{aligned}
SD(W_{kt}^*) &= \left(\frac{1}{25}\sum_{t=1}^{25}(W_{kt}^* - \overline{W}_k^*)^2\right)^{\frac{1}{2}} \\
&= \left(\frac{1}{25}\sum_{t=1}^{25}[W_{kt}^*]^2\right)^{\frac{1}{2}} \\
&= \left(\frac{1}{25}\sum_{t=1}^{25}\left[\frac{W_{kt} - \overline{W}_k}{SD(W_k)}\right]^2\right)^{\frac{1}{2}} \\
&= \frac{1}{SD(W_{kt})}\left(\frac{1}{25}\sum_{t=1}^{25}\left[W_{kt} - \overline{W}_k\right]^2\right)^{\frac{1}{2}} \\
&= \frac{1}{SD(W_{kt})}SD(W_{kt}) = 1
\end{aligned}
$$

Climate data

- This period predates the instrumental record.
- But, there is a record of things like; date of first frost, date of ice-free harbor, etc. that allow historians to reconstruct *regional* climates. NB: Icecores are global.
- This leads to decadal average measures of 'winter severity' by region.
- Denote this index of winter severity by T_{tk} (definition a little opaque).
- Calculate $T^*_{kt} = \frac{T_{kt} - \overline{T}_{kt}}{SD(T_{kt})}$. Also mean zero and SD of 1.

Trials vs. Temp I

We want to look at the relationship between T^*_{kt} and W^*_{kt}

- First,

$$W^*_{kt} = A_0 + A_1 t + A_2 t^2 + W^{**}_{kt}$$
$$T^*_{kt} = A_0 + A_1 t + A_2 t^2 + T^{**}_{kt}$$

- Why? These variables are now de-trended. We care about this if we think, e.g., there were fewer witch trials as technology improved slowly during the middle ages.

Trials vs. Temp II

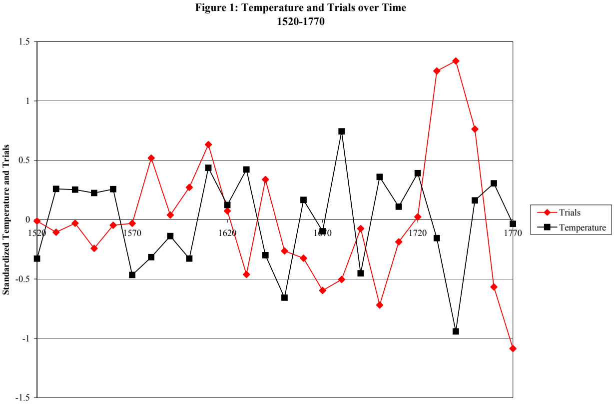
- Finally,

$$W_t^{***} = \frac{1}{11} \sum_{k=1}^{11} W_{kt}^{**}$$

$$T_t^{***} = \frac{1}{11} \sum_{k=1}^{11} T_{kt}^{**}$$

- These are mean (across regions) decadal deviations of temperature and trials from a quadratic trend, of the demeaned and normalized variables.
- They should not reflect region specific factors – they are demeaned.
- They should not reflect other trends in the data.

Plots of W_t^{***} and T_t^{***}



Trials are high when temperature is low.

Regressions

Estimating equations,

$$W^*_{kt} = A_0 + A_1 t + A_2 t^2 + A_3 T^*_{kt} + \varepsilon_{kt}$$

and

$$W^*_{kt} = A_t + A_3 T^*_{kt} + \varepsilon_{kt},$$

where A_t is 25 year fixed effects. That is, $\sum_{t=1}^{25} A_t \theta_t$ and θ_t is 1 in year t and 0 else.

Table 1[a]
Witchcraft Trials and Temperature
Dependent Variable: Witchcraft Trials Standardized by Region

	(1)	(2)	(3)	(4)
Standardized Combined Index	-0.212***		-0.206**	
	(2.59)		(2.32)	
Standardized Winter Severity Only		-0.179**		-0.292***
		(1.96)		(2.84)
Date	0.096	0.233***		
	(1.96)	(3.43)		
Date-Squared	-0.003	-0.011***		
	(1.43)	(3.45)		
Constant	-0.645**	-1.037***	-0.019	-0.059
	(2.39)	(3.16)	(0.26)	(0.71)
Decade Fixed Effects (1520-1770):	NO	NO	YES	YES
Observations	170	128	170	128
R-squared	0.10	0.15	0.24	0.28

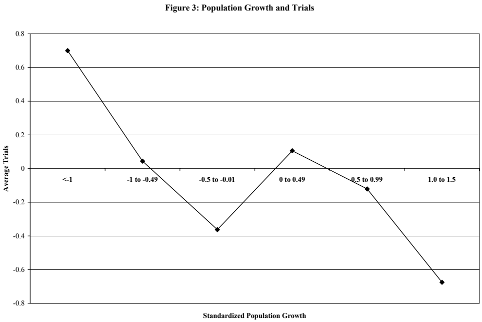
Absolute value of t-statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

- There is a pretty clear negative relationship between trials and temperature, condition of t.
- ... but b/c the variables have been transformed so many times it is hard to know the effect of, e.g, 1°of cooling.

Urban share vs Trials

- When the economy is most agricultural, if ag. productivity increases, so does urban population.
- Urban population is a measure of economic productivity.
- Use urban share and count of cities $>$ 10,000 to measure urban population.
- Data is available every 50 years.
- Calculate Population growth rates (%) and % growth in big cities.
- This gives growth rates for 5 periods and 11 regions. Aggregate trial data to 50 year periods, to match.

Trials vs population growth



- There are fewer trials when there is more population growth.
- ... witch trials actually tell us something about the whole state of the economy.

Summary

Long term climate change, cooling, pretty clearly had harmful effects. This is exactly the right sort of variation that we want to understand these effects, but...

- Warming not cooling.
- Pre-industrial Europe, not modern world.
- Funny outcome variable.
- Transformed temperature index is hard to relate to the RCPs we think about now.
- Can we compare these data to Zhang et al? Nope. They have been demeaned and detrended.

Population, adaption and climate in Iceland I

- Look at relationship between climate and population size in pre-industrial Iceland, 1720-1840.
- How do people adapt to climate change ? Is a cold shock worse if it follows a cold period or a warm period?

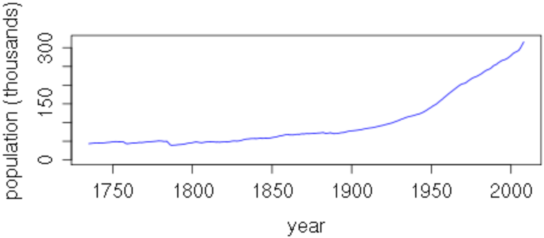
Background, 1720-1840, Iceland was

- Very poor. People mostly lived by raising sheep. There was a little fishing.
- Very little migration in or out. This was a policy of the Island's feudal rulers who wanted stability.
- Little technological progress – unusually so – again, this was a policy choice by feudal rulers who wanted stability.

So,

Population, adaption and climate in Iceland II

- Because so little else changed, if we see a relationship between population and climate, we can be pretty sure it's causal. We don't need to worry about climate shocks being mitigated by technological progress or migration.
- Because Iceland is poor, expect big effects.
- Finally, there is a long series of annual population data for Iceland, constructed from Church records. This is unusual.



Population was pretty stable until well into the industrial revolution.
Study the period before 1860.

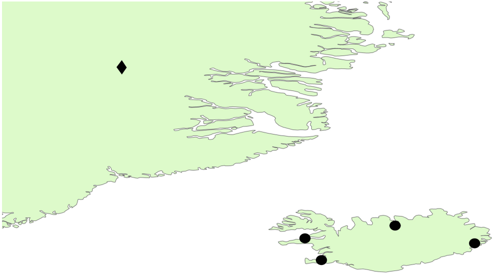
Climate data

- Between about 1920 and 1970, icecore and measured temperature records overlap.
- We use an icecore taken from nearby Greenland glaciers (see figures) and use them to impute a long time series of temperature.

$$Temp_t = A_0 + A_t Icecore_t + \varepsilon_t, \; t = 1910 - 1970$$
$$\widehat{Temp}_t = \widehat{A}_0 + \widehat{A}_1 Icecore_t, \; t = 1720 - 1860$$

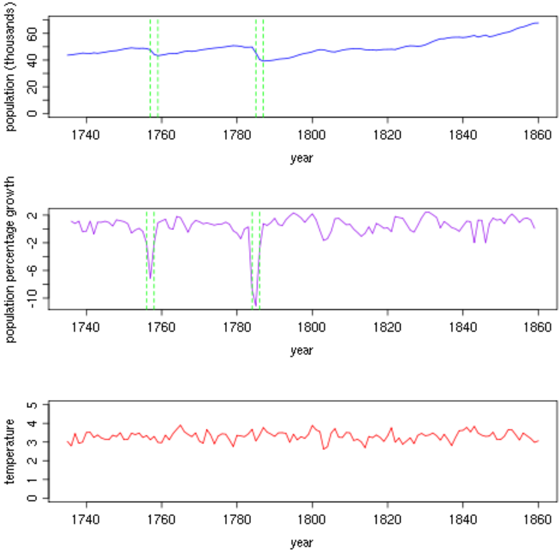
- This leaves us with a long series of both population and imputed temperature.

Icecore locations



Diamond is icecore, circles are weather stations.

Turner, AERPP 2012



Green is famines.

Population vs. temperature I

Define,

$$\Delta Pop_t = \frac{Pop_{t+1} - Pop_t}{Pop_t} \times 100$$
$$= \text{ \% change in pop}$$

Now define ‘lagged moving averages’,

$$MA2_t = \frac{1}{2}(Temp_t + Temp_{t-1}), \text{ or}$$
$$MAj_{t-1} = \frac{1}{j}(Temp_{t-i} + Temp_{t-i-1} + ... + Temp_{t-i-j})$$

We are interested in three types of regressions.

Population vs. temperature II

- ΔPop on short run climate. How important is recent climate? How many people starve in a cold year?
- ΔPop on long run climate (10-20 year average temp). How important is longer run climate? After many hard years, how much does the population shrink?
- ΔPop on long run $\times$ short run climate. Does the response to the shock depend on history? How much do people adapt to cold?

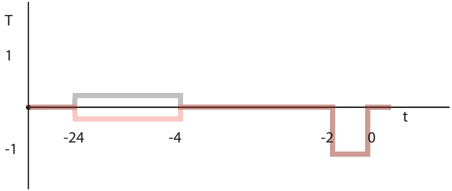
TABLE 1—NINE REGRESSIONS (ONE PER COLUMN) PREDICTING $(\Delta pop)_t$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{MA}2_t$	1.143***					1.153***	1.133***	1.084***	1.104***
	(0.359)					(0.355)	(0.353)	(0.323)	(0.298)
$\text{MA}5_t$		0.582							
		(0.721)							
$\text{MA}10_t$			1.172						
			(0.971)						
$\text{MA}10_{t-4}$				0.364		0.485		0.710	
				(1.051)		(1.017)		(1.044)	
$\text{MA}20_{t-4}$					-0.897		-0.208		-0.005
					(1.590)		(1.572)		(1.544)
$\text{MA}2_t \times \text{MA}10_{t-4}$								7.690*	
								(4.454)	
$\text{MA}2_t \times \text{MA}20_{t-4}$									11.10*
									(5.960)
pop_t	-0.089***	-0.091***	-0.086***	-0.090***	-0.093***	-0.087***	-0.089***	-0.092***	-0.093***
	(0.027)	(0.025)	(0.026)	(0.025)	(0.026)	(0.026)	(0.027)	(0.026)	(0.028)

Control variables in all regressions are: $time$, $time^2$, $(\Delta pop)_t$ and a constant.
Newey-West standard errors in parentheses. p-values: *** p<0.01, ** p<0.05, * p<0.1.

Columns 1-7 are regressions of ΔPop on recent on long run climate. Columns 8-9 involve interactions and are a little harder to understand.

Turner, AERPP 2012



- Consider two temperature histories, pink and grey.
- Grey: $MA2_t = -1$ and $MA20_{t-4} = 1/10$
- Pink: $MA2_t = -1$ and $MA20_{t-4} = -1/10$
- From Col 9,

$$\begin{aligned}\Delta Pop_t &= 1.104 MA2_t + (-0.005) MA20_{t-4} \\ &+ 11.1 (MA2_t \times MA20_{t-4}) \\ \Longrightarrow &\Delta Pop_t \approx -2.2, \text{ grey} \\ \Longrightarrow &\Delta Pop_t \approx 0, \text{ pink}\end{aligned}$$

- Two cold winters following 20 years of warm causes a 2% decrease in population. Two cold winters following 20 years of cold has almost no effect.
- Icelanders ‘adapt’ to colder climate over about a generation.

Issues:

- Non-linearities mean the magnitude of the adaption process is sensitive to magnitudes.
- Be suspicious. Data quality is poor.
- Lagged population should affect current population directly. This would need a model.
- How relevant is pre-industrial Iceland to anything?
- If we can really adapt to a new climate in a generation, that seems pretty important. Some of the adaptations are ‘getting smaller’, and so are pretty costly.

Economic effects of long-term climate change

This is similar to the other little ice-age papers, but

- most of Europe
- sheds more light on mechanisms
- provides nice evidence of adaptation

Data I

- Population of 2191 European cities with Pop$>$5000 sometime between 800 and 1850, for 1600, 1700, 1750.
- Gridded annual temp from most of Europe for 50km^2. From many sources, much like Oster's data, but now available in a grid.
- Drop cities in Far Eastern Europe and with missing temp, $N = 2120$.
- Define temperature as

$$Temp_{it} = \begin{cases} \frac{1}{100}\sum_{\tau=1}^{100} Temperature_{it-\tau} & \text{for 1600 and 1700} \\ \frac{1}{50}\sum_{\tau=1}^{50} Temperature_{it-\tau} & \text{for 1750, 1800, 1850} \end{cases}$$

- main outcome measure is $\ln(citypop)$.
- Yield Ratio is also important. This is Harvest/Sewn. Annual data from 12 countries from about 1500 to about 1750.

Little Ice Age in Northern Hemisphere

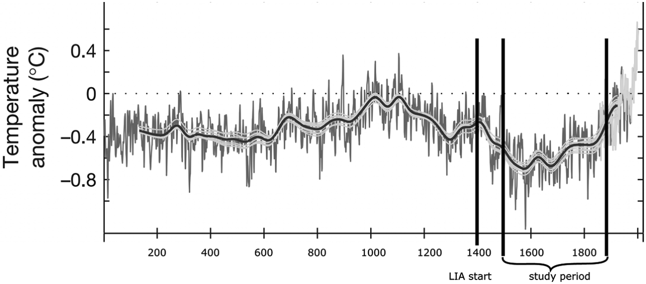


FIG. 1. Temperature over the past 2,000 years. This figure shows the temperature graph "Estimations of Northern Hemisphere Mean Temperature Variations" from Moberg et al. (2005) with some modifications: a vertical black bar "Little Ice Age (LIA) start" and two black bars "study period" (this is the time period for which I have temperature data), and years on the *x* axis have been added. In the original article, the graph is part of a larger graphic.

Little Ice Age in 2120 cities

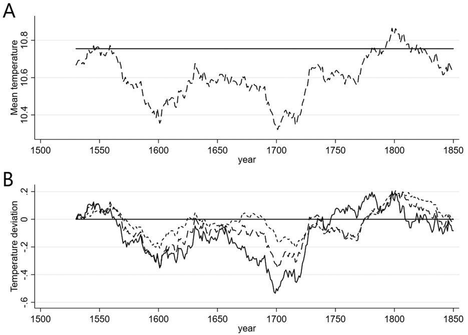


FIG. 2. Temperature variation over the study period. *A*, Mean temperature (30 year moving average) over the course of the study period (dashed line). The solid line is the temperature mean from 1900 to 1950, after the end of the Little Ice Age and before the onset of global warming. *B*, Changes in the long term mean in temperature for three groups of cities: cities with strong cooling (below the 25th percentile in temperature change; solid line) and with weak cooling (above the 75th percentile in temperature change; short dashed line) and cities with moderate cooling (between the 25th and 75th percentile in temperature change; long dashed line) in the seventeenth century. The solid line is the temperature mean from 1500 to 1530 from which temperature deviations are measured.

Note: 25% in 1700 $\approx -.2$℃. 75% in 1700 $\approx -.4$℃.

TABLE 1
Summary Statistics

	All Cities (1)	Cities with Strong Cooling (2)	Cities with Weak Cooling (3)
City size in 1600	5.680	4.898	6.471
	(14.617)	(13.977)	(15.195)
Mean temperature in 1600	9.255	6.658	11.850
	(3.589)	(1.635)	(3.098)
City growth, 1600 1850	13.051	17.589	8.514
	(55.198)	(74.928)	(21.001)
Geographic control variables:			
Altitude	238.804	142.622	335.351
	(262.043)	(143.435)	(313.607)
Ruggedness	.126	.069	.183
	(.161)	(.081)	(.197)
Potato suitability	29.724	35.344	24.083
	(16.509)	(18.028)	(12.508)
Wheat suitability	43.273	49.189	37.334
	(22.018)	(22.880)	(19.383)
Historical control variables:			
Protestant Reformation:			
Catholic	.638	.414	.863
	(.481)	(.493)	(.344)
Lutheran	.126	.252	.000
	(.332)	(.434)	(.000)
Calvinist/Huguenot	.121	.110	.132
	(.326)	(.313)	(.339)

Note. Data on city size, temperature, and control variables were collected from various sources as described in sec. II. Cities with strong cooling are cities that experienced a rel atively large (above median) decrease in long term mean temperature from the sixteenth to the seventeenth century. Cities with weak cooling are cities that experienced a relatively small (below median) decrease in long term mean temperature between the sixteenth cen tury (when my data start) and the height of the Little Ice Age in the seventeenth century.

Cities that got colder are smaller, colder and grow faster (city size in thousands, growth rate is % change from 1600-1850).

Estimating equation I

$$\ln(\text{City Pop})_{it} = \gamma Temp_{it} + a_t + l_i + x_{it} + \varepsilon_{it}$$

Want γ. a_t is year fixed effects, l_i is city fixed effects, x_{it} is control variables.

This is (almost) a difference in difference estimator.

Consider a simpler case where: $t = 1, 2$; $T_{it} = T^L, T^H$; $E(\varepsilon_{it}) = 0$ and $x_{it} = 0$. Write $Temp_{it} = T_{it}$ and $\ln(\text{City Pop})_{it} = Y_{it}$. Finally, suppose that all units have $T_{i1} = T^L$.

Estimating equation II

Then for observations that don't change temperature,

$$E(Y_{i1}|T_{i2} = T^L) = \gamma T^L + a_1 + I_i$$
$$E(Y_{i2}|T_{i2} = T^L) = \gamma T^L + a_2 + I_i$$

so that

$$\begin{aligned} & E(Y_{i2}|T_{i2} = T^L) - E(Y_{i1}|T_{i2} = T^L) \\ & = (\gamma T^L + a_2 + I_i) - (\gamma T^L + a_1 + I_i) \\ & = a_2 - a_1 \end{aligned}$$

Estimating equation III

and for observations that get colder,

$$E(Y_{i1}|T_{i2} = T^H) = \gamma T^L + a_1 + l_i$$
$$E(Y_{i2}|T_{i2} = T^H) = \gamma T^H + a_2 + l_i$$

so that

$$\begin{aligned}
&E(Y_{i2}|T_{i2} = T^H) - E(Y_{i1}|T_{i2} = T^L) \\
&= (\gamma T^H + a_2 + l_i) - (\gamma T^L + a_1 + l_i) \\
&= (a_2 - a_1) + \gamma(T^H - T^L)
\end{aligned}$$

Estimating equation IV

Then the difference in these two differences gives us our estimate

$$
\begin{aligned}
&(E(Y_{i2}|T_{i2}=T^H)-E(Y_{i1}|T_{i2}=T^L)) \\
&\qquad\qquad -(E(Y_{i2}|T_{i2}=T^L)-E(Y_{i1}|T_{i2}=T^L)) \\
&\quad =((a_2-a_1)+\gamma(T^H-T^L))-(a_2-a_1) \\
&\quad =\gamma(T^H-T^L)
\end{aligned}
$$

and we know (T^H-T^L), so this difference in differences gives us our estimate of the treatment effect.

This is what Waldingner is doing, except that she has also got x_{it} in the regressions. What does this do?

Estimating equation V

Suppose $x_{it} = 0, 1$. Then we are going through this whole process twice, once for $x_{it} = 1$ and once for $x_{it} = 1$, and averaging the resulting estimates of γ.

City size vs. Temperature I

TABLE 2
Temperature and City Size

	log City Size					
	(1)	(2)	(3)	(4)	(5)	(6)
Mean temperature	.532	.724	.749	.931	.842	1.17
Standard error clusters:						
Assuming spatial and serial autocorrelation	(.262)**	(.268)***	(.269)***	(.328)***	(.265)***	(.429)***
Two way (city and region × time period)	(.281)*	(.282)**	(.283)**	(.323)***	(.276)***	(.465)**
Temperature grid	(.193)***	(.212)***	(.213)***	(.274)***	(.211)***	(.386)***
Control variables:						
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country in 1600 linear time trend					Yes	
Country in 1600 × time period fixed effects						Yes
Historical controls (× time period fixed effects)	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls (× time period fixed effects)		Yes	Yes	Yes	Yes	Yes
Sample	All	All	Excluding capital cities	Excluding ocean cities	All	All
Observations	10,600	10,600	10,510	8,395	10,600	10,600
R^2	.767	.769	.759	.766	.779	.783

Note. Observations are at the city time period level. Regressions in cols. 1, 2, 5, and 6 use a baseline sample of 2,120 cities. Capital cities are excluded in col. 3, and cities located less than 10 km from an ocean are excluded in col. 4. The time periods are 1600, 1700, 1750, 1800, and 1850. The dependent variable is the natural log of the number of city inhabitants. "Mean temperature" is year temperature averaged over the periods 1500 1600, 1600 1700, 1700 1750, 1750 1800, and 1800 1850. Information on three types of standard errors are provided: (1) standard errors assuming both serial and spatial correlation (following Conley 2008), (2) two way clustered standard errors at the temperature grid level and the region × time period level, and (3) standard errors clustered at the temperature grid level of the underlying temperature data. All specifications include city and time period fixed effects. Column 5 additionally includes country linear time trends, and col. 6 includes country × time period fixed effects. Historical control variables are a city's religious denomination in 1600 (Catholic, Catholic after the Counter Reformation, Lutheran, Anglican, Calvinist/Huguenot, or Calvinist/Lutheran), whether a city was a university town in 1500, whether a city was part of a country engaged in Atlantic trade, whether a city was part of the Roman Empire in year 1 CE, a city's distance to the nearest Roman road, and a city's distance to the ocean. Five geographic control variables control for the city's altitude, its soil suitability for wheat cultivation, its soil suitability for potato cultivation, ruggedness, and precipitation. All control variables are interacted with time period indicator variables.

* $p < .1$.
** $p < .05$.
*** $p < .01$.

$$\ln(\text{City Pop})_{it} = \gamma Temp_{it} + a_t + I_i + x_{it} + \varepsilon_{it}$$

City size vs. Temperature II

How big is this effect?

$$
\begin{aligned}
\ln Y^0 &= 0.53T + a_t + l_i + x_{it} \\
\ln Y^1 &= 0.53(T + 0.2) + a_t + l_i + x_{it} \\
\implies \ln Y^1 - \ln Y^0 &= 0.53 \times 0.2 \\
\implies \ln(Y^1 / Y^0) &= 0.01060 \\
\implies Y^1 / Y^0 &= e^{0.0106} = 1.01066
\end{aligned}
$$

So $0.2°C$ cooler shrinks cities by about 1%.

$0.2°C$ is about half the little ice age effect.

1% of city size is about 1/13 of total growth from 1600-1850.

City size vs. Temperature III

This is a small effect. Cities that get colder, grow a little more slowly.

Plot of residuals I

Suppose we estimate

$$\ln(\text{City Pop})_{it} = a_t + l_i + x_{it} + \varepsilon_{it}$$

and

$$T_{it} = a_t + l_i + x_{it} + \mu_{it}$$

Then ε_{it} and μ_{it} are population and temperature ‘corrected’ for individual means and annual variation. That is, they should be more ‘alike’ than the raw data. If we compare them, we should be able to see how city size ad temperature are related. (in fact, the Frisch-Waugh Theorem says the slope of this line will be the same as in our original regression).

Plot of residuals II

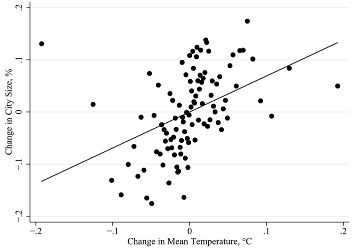


FIG. 3. Change in mean temperature versus change in city size. This figure displays a binned scatterplot corresponding to the estimates from column 2 of table 2. I residualize log City Size and mean temperature with respect to city fixed effects, time period fixed ef fects, historical, and geographic control variables using an ordinary least squares regres sion. I then divide the sample into 100 equally sized groups and plot the mean of the *y* residuals against the mean of the *x* residuals in each bin.

This plot shows corrected city sixe on the y-axis, and corrected temp on the x-axis. The slope should match column 2 of table 2. Cities that cooled more, grew more slowly. This is not what you would have guessed from the raw data in table 1.

Yield ratio vs. Temperature I

- Yield ratio is ratio of harvest to seed.
- Regression equation

$$\text{Yield Ratio}_{it} = A + BT_{it} + \textit{year} + \textit{location} + \varepsilon$$

Yield ratio vs. Temperature II

TABLE 3
TEMPERATURE, YEARLY YIELD RATIOS, AND WHEAT PRICES

Variable	Yield Ratio (1)	Wheat Prices (2)	Yield Ratio (3)	Wheat Prices (4)
Mean temperature	.430***	−.111***		
	(.115)	(.0283)		
Growing season temperature			.364***	−.115***
Season τ			(.116)	(.0221)
Nongrowing season temperature			−.148	.0303*
Season τ			(.0952)	(.0171)
Growing season temperature				−.0993***
Season $\tau - 1$				(.0191)
Nongrowing season temperature				−.0151
Season $\tau - 1$				(.0166)
City fixed effects	Yes	Yes	Yes	Yes
Decade fixed effects	Yes		Yes	
Year fixed effects		Yes		Yes
Control variables (× year fixed effects)	Yes	Yes	Yes	Yes
Observations	205	2,731	205	2,714
R^2	.231	.684	.217	.682
Number of bootstrap units	12	10	12	10
Number of repetitions	999	999	999	999

NOTE. The outcome variable "Yield Ratio" is defined as the ratio of harvested crop grains to the crops used for sowing. The outcome variable "Wheat Prices" is the natural log of wheat prices. "Mean temperature" is temperature averaged over the same year. "Growing season temperature" is temperature during spring and summer of year τ. "Nongrowing season temperature" is temperature during the fall of year $\tau - 1$ and the winter of year τ. I omit all locations from the yield data sample with fewer than 10 independent data points. The final yield data sample includes 12 cities in four European countries: France, Germany, Poland, and Sweden. Wheat price data are for Amsterdam (282 years), Antwerp (133 years), Leipzig (215 years), London (351 years), Madrid (274 years), Munich (253 years), Naples (248 years), Florence (305 years), Paris (334 years), and Strasbourg (336 years). Bootstrapped standard errors are clustered at the city level. The control variable "Access to Ocean" is an indicator variable that is one for all cities located less than 10 km from the ocean. The control variable "Atlantic Trader" is an indicator variable that is one for all locations in countries engaging in Atlantic trade. These control variables are interacted with time period indicator variables.

Yield ratio vs. Temperature III

Note that coefficient in population regressions and yield regressions are about the same. Should we expect this? Hint: about 90% of population was rural/agricultural.

Value of trade vs. Temperature I

- Did cities trade more in response to colder weather?
- To check let Y_{it} be number of ships arriving (and recorded as paying customs taxes). Look at effect of long lagged averages of temperature.

$$Y_{it} = \gamma_0 \frac{1}{25} \sum_{k=0}^{24} Temp_{it} + a_t + l_i + x_{it} + \varepsilon_{it}$$

Value of trade vs. Temperature II

TABLE 5

Temperature and Trade (Number of Ship Arrivals)

	ln Number of Ships							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Growing season temperature in $t-1$ to $t-5$	−.101				−.159			
	(.0774)				(.163)			
Nongrowing season temperature in $t-1$ to $t-5$	.0516				.182*			
	(.0505)				(.108)			
Growing season temperature in $t-1$ to $t-25$		−.758***				−1.754***		
		(.277)				(.569)		
Nongrowing season temperature in $t-1$ to $t-25$		.00971				.537		
		(.187)				(.406)		
Growing season temperature in $t-1$ to $t-50$			−1.362***				−2.734***	
			(.422)				(.843)	
Nongrowing season temperature in $t-1$ to $t-50$			−.230				.497	
			(.281)				(.586)	
Growing season temperature in $t-1$ to $t-100$				−1.984**				−5.500***
				(.776)				(1.457)
Nongrowing season temperature in $t-1$ to $t-100$				−.715				−.0791
				(.576)				(1.228)
Destination port fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Distance to other cities	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City size					Yes	Yes	Yes	Yes
Control variables (× 50 year period fixed effects)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	202,920	202,920	202,920	202,920	58,740	58,740	58,740	58,740
R^2	.267	.268	.268	.268	.442	.442	.443	.444
Number of destination ports	760	760	760	760	220	220	220	220

Note. Observations are at the destination port year level, with data for 760 destination ports and the years 1591 1857. The dependent variable is the natural log of the number of ship passages arriving at port i in year t. "Growing season temperature" in year t is temperature during spring and summer of year t. "Nongrowing season temperature" in year t is temperature in the fall of year $t-1$ and the winter of year t. All specifications include destination port fixed effects, year fixed effects, and geographic and historical control variables interacted with decade fixed effects. Historical controls include informa tion on a country's religious denomination in 1600 (for details, see table 2), whether a country had a university town in 1500, whether it was engaging in Atlantic trade, whether it was part of the Roman Empire in year 1 CE, and its distance to the ocean. Five geographic control variables control for the country's mean altitude, its mean soil suitability for wheat cultivation, its mean soil suitability for potato cultivation, and mean ruggedness. Standard er rors are clustered at the level of the temperature grid cell of the underlying temperature data.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

Value of trade vs. Temperature III

After 25+ years, cities that saw temperature decreases, increased trade. This suggests that trade was an adaptation to deteriorating climate.

It is statistically important. Is it economically important?

City size vs. Temperature/trade I

Estimating equation,

$$\ln(\text{City Pop})_{it} = \gamma_0 \mathit{Temp}_{it} \beta + \gamma_1 \mathit{Temp}_{it} \times \mathit{Trade}_{it} + a_t + l_i + x_{it} + \varepsilon_{it}$$

City size vs. Temperature/trade II

TABLE 6
Heterogeneity in the Effect of Temperature

		Sound Toll Trade		Hanseatic Trade	
	(1)	(2)	(3)	(4)	(5)
Mean temperature	.724***	.865***	.872***	.740***	.855***
	(.189)	(.210)	(.210)	(.190)	(.208)
Mean temperature × trade		−.688***		−.956***	
		(.187)		(.174)	
Mean temperature × number of trade partners <25th percentile			−.386		−.578*
			(.328)		(.324)
Mean temperature × number of trade partners >25th percentile			−.783***		−.688***
			(.188)		(.189)
Observations	10,600	10,600	10,600	10,600	10,600
R^2	.485	.486	.486	.486	.486
Number of cities	2,120	2,120	2,120	2,120	2,120

Note. Column 1 reports ordinary least squares estimates of the main specification (identical to col. 2 in table 2) for comparison. Column 2 shows results when including an interaction term between "Mean temperature" and "Sound Toll Trade," an indicator variable that is one for all cities that were destination cities in the Sound toll trade. Column 3 shows results when including two interaction terms: one interaction term between "Mean temperature" and the indicator variable "number of trade partners <25th percentile," which is one for all cities in the Sound toll trade network whose number of trading partners was below or equal to the 25th percentile, and another interaction term between "Mean temperature" and the indicator variable "number of trade partners >25th percentile," which is one for all cities whose number of trading partners exceeded the 25th percentile. Standard errors are clustered at the temperature grid level of the underlying temperature data. All specifications include city and time period fixed effects. Historical and geographical controls are as defined in table 2. All control variables are interacted with time period indicator variables.

Cities with good access to inland trade experience almost no harm from cooling. Trade allows almost complete adaptation.

This seems really important.

Conclusion I

- Climate change, colder, is bad,
  - Zhang et al, $\Longrightarrow$ conflict
  - Oster $\Longrightarrow$ witch trials
  - Turner et al., Waldinger $\Longrightarrow$ fewer people
- Turner: -1° C for 20 years $\Longrightarrow$ population falls by 9%. Compounding to get a 100 year effect, we have $(1 - 0.09)^5 = 0.62$, so after 100 years of cold, population is only 62% of original – not allowing for adaptation.
- Waldinger: -1° C for 100 years $\Longrightarrow$ city population shrinks by a factor of 0.58 ($e^{-0.53}$). Note close agreement between Waldinger and Turner et al.

Conclusion II

- In Iceland there were few opportunities for adaption. No migration. little trade, little progress. Adaption was probably costly; smaller bodies and living closer to domestic animals.
- Climate change was clearly stressful for humans, but these papers suggest that adaption was possible and pretty quick, even for pre-industrial societies.
- Issues,
  - Did trading cities benefit at the expense of their hinterlands?
  - Does medieval history tell us anything useful about the world today?
  - Beware, data quality is not great in any of these papers.