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Short- and long-term impacts of climate variations on the agrarian economy in pre-industrial Europe

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ABSTRACT: Only a small number of quantitative studies have investigated the short- and long-term impacts of climate variations on society during Europe's pre-industrial era. Accordingly, there is a lack of research clearly comparing the consequences of climate variation (short-term) and climate change (long-term). This study focuses on the close relationship between climate variations and the dynamics of the agrarian economy in Europe during the period of 1500 to 1800 AD. ARX modeling was applied to analyze the relationship between climate and past agrarian economies, on large spatial and long temporal scales. Both short- and long-term findings are provided, based on statistical analysis, as well as the empirical study of the 17th century economic crisis as a case analysis. The negative climatic variations in the short-term caused grain prices to increase. Grain prices were affected for up to 25 yr by a period of climatic variation due to the price stickiness. The immediate and long-term effects of climate variations over the study period can add up to significantly influence agrarian economies. Climate change occurs when climate variations last for more than 30 yr. The accumulated effect of climate change on the agrarian economy ultimately resulted in an economic crisis in pre-industrial Europe.

KEY WORDS: Climate change · Grain market · Europe · Pre-industrial era · ARX modeling

1. INTRODUCTION

The consequences of climate variation at different temporal scales have attracted a great deal of scholarly attention (Patz 2002, Parmesan & Yohe 2003, Ludwig et al. 2006). Both short- and long-term climate variations can bring unwanted disasters to the world. Extreme climatic fluctuations can result in widespread economic loss or even death (Easterling et al. 2000, Mirza 2003), consequences that have warranted increased research interest in the effect of sudden climate instabilities (Karl & Easterling 1999). Climate variation that continues for ≥30 yr is formally defined as climate change (Wittwer 1995, IPCC 2007); such climate change is capable of initiating economic crises and social disasters (Steensgaard 1997, Zhang et al. 2007a, 2011a,b, Tol & Wagner 2010).

Although climate fluctuations affect society on different scales (Clark 1985), only a limited number of studies have quantitatively detected the short- and long-term impacts of climate variations on society during the pre-industrial era. In addition, there is inadequate research clearly comparing the consequences of climate variation (short-term) and climate change (long-term). Zhang et al. (2011b) showed that climate change can ultimately cause a social crisis (e.g. social disturbances, wars, famines and epidemics) through its effect on an economy, as was the case with turmoil in pre-industrial Europe. Accordingly, this study aims to examine the associations between climate and the agrarian economy at differ-

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ent temporal scales in pre-industrial Europe, when the grain market was a major economic driver.

Past research has shown that conducting an investigation on a large geographic scale can help us understand the complex interactions between nature and human society (Miller 1990, Butlin 1993, MacDonald 1998). In addition, focusing on a specific socioeconomic period (i.e. pre-industrial Europe) can also help us to interpret the relationship between these factors. Europe holds detailed historic records on climatic conditions (Jones & Bradley 1995) as well as crop cultivation (Hartmann et al. 1981); therefore, all of Europe was taken as the area of study for this research. We limited our study period to 1500 AD to 1800 AD because of the abundance of detailed records during this particular era. Furthermore, this time period overlaps with the Little Ice Age (Grove 1988, Osborn & Briffa 2006), a well-documented period when food production was severely scarce (Ewert et al. 2007). This period also encompassed the General Crisis of the 17th Century: the years from 1590 to 1660 AD (Parker & Smith 1978, Fischer 1996), during which the lowest temperatures of the past millennium were experienced (Luterbacher et al. 2004, Osborn & Briffa 2006).

We chose to use the ARX — an autoregressive model with exogenous terms. It can capture and reflect the variations in temporally changing systems to meet theoretical and practical interests (Qin et al. 2010), and it is also useful in simulating the influence of past conditions and external systems (independent variables) on changing temporal factors (Hamilton 1994). Moreover, the ARX model is regarded as extremely suitable for control theories with simpler estimation in signal studies and engineering (Huusom et al. 2010). For example, it has been widely adopted in modeling wind power at different time scales (Durán et al. 2007), structural health monitoring (Fasel et al. 2003), and pipeline leak detection (Vaz Junior et al. 2010). In the social sciences, the ARX model has also been used to simulate human driving behavior (Suzuki et al. 2005); even though these studies are very limited, the potential of the ARX modelling in this area is very promising.

We used the ARX model to simulate the short- and long-term effects of climate variation on the agrarian economy in pre-industrial Europe. By analyzing the 17th century macroeconomic crisis as a case application, we compared the different consequences — based on results from the simulation — of the effects of climate variations and climate change. We present a new perspective to quantitatively explain the 17th century crisis in a combination of short- and long-term scales through the use of statistical modeling. Given that our research goal is to examine the associations between climate and the agrarian economy on a long-term and continental scale, we ignore individual incidents or events that could temporarily distort the functioning of the grain market. We believe that this broad ranging approach, although not without limitations, suits the scope of this study.

2. DATA AND METHODS

The real price of grain (adjusted for inflation) as the core indicator of the grain market was ultimately influenced by climate and population size in pre-industrial Europe (Zhang et al. 2011b). A large number of studies show that supply was reduced by decreased production from adverse climatic conditions, leading to higher prices under the pressure of population demand. However, these studies focused on specific countries, such as England (Appleby 1979, Campbell 2010), Poland (Stone 2001), Germany (Fulbrook 2004), France and Russia (Pennington 1989). In contrast, our study adopts climate and population as factors stimulating the grain price in the entire European grain market from 1500 to 1800 AD based on recent research (Zhang et al. 2011b).

2.1. Data sources

Temperature. The temperature anomaly series in Europe was derived from 2 authoritative annual temperature reconstructions: (1) the annual temperature reconstruction for European land areas conducted by Luterbacher et al. (2004), which covers European land areas (25° W to 40° E and 35° N to 70° N) spanning the period of 1500–2003 AD; and (2) the annual temperature dataset in which the regional temperature series nested within Europe was combined by Osborn & Briffa (2006), specifically based on data from the regions of western Greenland, Netherlands/Belgium, Austria, northern Sweden, northwestern and northern Russia.

These 2 temperature reconstructions were derived from different proxies, and were conducted by using various methods on data from the entire European continent. Therefore, both were mathematically normalized to homogenize the original variability. This transformation could not preserve the initial numerical values of variation, but could provide a reliable relative amplitude of temperature change. The 2 normalized series were then arithmetically averaged to generate the Europe temperature composite used in this study, which was applied as the paleo-temperature reconstruction method at the same geographic scale (Mann & Jones 2003). This temperature reconstruction has been used to justify the causal relationships between climate change and social crises in pre-industrial Europe (Zhang et al. 2011b).

Precipitation. This variable was not included in any previous study on the relationship between climate and social crises (Zhang et al. 2011a,b). Therefore, to advance the findings on the relationship between climate and society, precipitation is included in this analysis. The precipitation anomaly series in Europe was derived from the latest reconstructions based on tree-ring data (Büntgen et al. 2011), which has a high resolution on an annual scale.

Population size. This study is not principally demographic research; however, population is included as an independent variable to follow recent research (Zhang et al. 2011b). In this study, the population size of Europe was extracted from the Atlas of World Population History (McEvedy & Jones 1978). Given that the population data were obtained at irregular time intervals, the common logarithm of the data points was taken, linearly interpolated, and anti-logged back to create an annual time series. This method avoids any distortions of the population growth rate resulting from the data interpolation process.

Real price of grain. The real price, rather than the nominal price, must be adopted to adjust for the inflation rate when prices are studied over a long period of time (Pindyck & Rubinfeld 1995) because inflation can increase price levels (Spencer & Amos 1993) and the nominal price cannot reflect the actual cost (Browning & Zupan 1996). Only by adopting the real price for this analysis can we consistently reflect the value of commodities (Landsburg 1999). Therefore, the real price of grain is adopted, which is also regarded as a key indicator of social well-being (Zhang et al. 2011b). The real price is calculated as follows:

$$RP_t = \frac{CPI_{\text{Base Year}}}{CPI_t} \times P_t \quad (1)$$

where RP represents the real price of grain, CPI stands for the Consumer Price Index, P represents the nominal grain price, t is the time step, and the base year is 1500 AD.

In this analysis, the nominal grain price series was derived from the website of the International Institute of Social History (www.iisg.nl/hpw/data.php#europe). The price data included 4 grain types (wheat, rye, barley, and oats) in 16 major European regions. The unit of measure was grams of silver per liter. To construct the grain price series, the prices of wheat, rye, barley, and oats were calculated by arithmetically averaging the price data for each grain in the 16 regions. Grain is a basic necessity for human consumption, for which there is no effective substitute; this was especially the case in pre-industrial Europe (van Bath 1963, Spencer & Amos 1993, McConnell & Bruce 2002). Therefore, we considered these 4 kinds of crops together as one group. The annual price series of the 4 types of grains were then arithmetically averaged. Any missing data were linearly interpolated to obtain an annual time series. The averaged data can eliminate noise and achieve a more accurate trend, which is consistent with climate data series.

The agrarian economy in pre-industrial Europe was only slightly affected by international trade, which in theory could help stabilize prices to a certain extent. Given chronological constraints and the high costs of spatial transport, limited efforts were taken to dampen price volatility (Persson 1996). Government intervention in the past helped to relieve recurrent price shocks due to temporary grain shortages (Ewert et al. 2007); however, it did not provide considerable support if the grain shortage occurred at an extremely large regional scale (Zhang et al. 2007a).

The CPI measures the cost for a typical family to buy a representative basket of goods for daily needs, including wheat, barley, oats, rye, beef, peas, cheese, eggs, oil, honey, coal, beans, sugar, butter, and other goods. It is consequently referred to as the cost-of-living index (Hubbard & O'Brien 2009). CPI data were obtained from the Allen-Unger Global Commodity Prices Database (www.history.ubc.ca/faculty/unger/ECPdb/index.html).

See Fig. 6 for all 4 data series; namely, temperature anomaly, precipitation anomaly, real price of grain, and population size.

2.2. Granger causality analysis

Granger causality analysis (GCA) is considered an effective method to build causal relationships (Sobel 2000, Russo 2009). It was adopted in this study to justify the causal relationships between 3 pairs of data series: (1) temperature and real price of grain; (2) precipitation and real price of grain; and (3) population and real price of grain.

Granger's definition of probabilistic causality assumes 2 fundamental principles: (1) the cause must precede the effect in time, and (2) the causal series should contain 'special' information which can imply and forecast the series more effectively than if it is only being explained by the caused series itself (Granger 1988). This study meets the above criteria; therefore, GCA was applied. The GCA proposes a 2-variable causal model with 2 stationary time series, X_t and Y_t, with zero means (Granger 1969):

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t \quad (2)$$

where, a and b are the coefficients of the time series. j is the data of the time series at time point j, and m is the length of the time series which is set based on lag. ε is the residue and t is the time step.

Given that the model was set for a stationary data series, the Augmented Dickey–Fuller (ADF) test was used before GCA for the stationarity checking of the variables. Differencing was used on both series to achieve the stationary property (Ahmad & Harnhirun 1996, Thornton 2001). The ADF approach controls higher-order correlation by adding lagged difference terms of the dependent variable Y to the right-hand side of the regression, which can be written as the following equation (Agung 2009):

$$DY_t = \mu + \delta Y_{t-1} + \beta_1 DY_{t-1} + \beta_2 DY_{t-2} + \ldots + \beta_p DY_{t-p} + \varepsilon_t \quad (3)$$

where

$$DY_t = Y_t - Y_{t-1} \quad (4)$$

where μ is the intercept of the equation, β is the coefficient of the time series and p is the data of the time series at time point p. D means the differencing. ε is the residue and t is the time step.

The null hypothesis of the series $\{Y_t\}$ has a unit root, that is, H_0: $\delta = 0$.

In the ADF test, the upper bound of the lag length should be specified. This value can be substituted by any positive integer value (according to different rules). Alternatively, the maximum lag can be chosen based on the following statistical formula (Hayashi 2000):

$$\text{Lag}_{\text{Max}} = \text{int}\left[12 \times \left(\frac{T}{100}\right)^{0.25}\right] \quad (5)$$

where int is the integer.

After applying the ADF test on the stationarity status of each data series, the lag length should be selected for the GCA. In the model, the lags of X_t and Y_t are set equally. Given that the t or F statistic is only a function, it depends on the correlation between the 2 variables and the set of conditioning variables. If the lag is set the same, then the same conditioning variables can be included (Kirchgässner & Wolters 2007). However, how to set the lags for analysis is another issue. Arbitrary selection of the lag has been criticized in causality analysis on the grounds of the statistical results being often sensitive to the lag length (Hsiao 1979, 1981). Therefore, in this study, the Schwarz Bayesian information criterion (BIC) was adopted for the lag selections. The application of BIC has been suggested in GCA of large sample sizes (Mills & Prasad 1992, Enders 1995). The formula for calculating the BIC is as follows (Schwarz 1978, Liddle 2007):

$$\text{BIC(m)} = -2\ln(L) + m\ln(N) \quad 1 \le m \le m_{\max} \quad (6)$$

where L is the maximum likelihood achievable by the model, m is the number of parameters of the model, and N is the number of data points used in the fit.

m_{max} is the maximum lag, which can be chosen based on Eq. (5). We obtain the m for the BIC lag in the ADF test and then apply m to set the lag in Eq. (2) for the GCA.

2.3. Modeling

In this study, the ARX modeling method was adopted to simulate the effect of climate on the grain market in pre-industrial Europe. This method is useful in simulating the influence of past conditions and external systems (i.e. independent variables) on the dependent variable (Hamilton 1994, Huusom et al. 2010, Qin et al. 2010).

$$Y_t = \beta_0 + \beta_1 x_{t1} + \beta_2 x_{t2} + \ldots + \beta_q x_{tq} + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t \qquad t = 1,2,3,\ldots n \quad (7)$$

where β and ϕ are coefficients of the time series, p and q are the data of the time series at time point p, ε is the residue, and t is the time step. Y: dependent variable, x: independent variable.

Through model parameter estimation, the above ARX model is expressed as follows:

$$\hat{Y}_t = \hat{\beta}_0 + \hat{\beta}_1 x_{t1} + \hat{\beta}_2 x_{t2} + \ldots + \hat{\beta}_q x_{tq} + \hat{\phi}_1 Y_{t-1} + \hat{\phi}_2 Y_{t-2} + \ldots + \hat{\phi}_p Y_{t-p} \quad (8)$$

3. RESULTS

3.1. GCA on the associations

We formed the causal linkages (i.e. null hypotheses) that temperature, precipitation and population do not Granger cause the real price of grain.

The ADF test includes the calculations of the trends and intercept of the data series. Table 1 presents the

Table 1. Augmented Dickey–Fuller test results

Series	Probability		
	No Difference	1st Difference	2nd Difference
TEMPERATURE	0.0037	0.0000	0.0000
PRECIPITATION	0.0000	0.0000	0.0000
POPULATION	0.9998	0.6187	0.0000
REAL PRICE OF GRAIN	0.0004	0.0000	0.0000

Table 2. Difference level and Schwarz Bayesian information criterion lag of causal linkages

Group	Difference level	BIC Lag
TEMPERATURE → REAL PRICE OF GRAIN	No Difference	2
PRECIPITATION → REAL PRICE OF GRAIN	No Difference	2
POPULATION → REAL PRICE OF GRAIN	2nd Difference	14

Table 3. Granger causality analysis results

Null hypothesis	*F*	p
TEMPERATURE does not Granger cause REAL PRICE OF GRAIN[a]	8.558	<0.001
PRECIPITATION does not Granger cause REAL PRICE OF GRAIN[a]	1.73691	0.178
POPULATION does not Granger cause REAL PRICE OF GRAIN[b]	4.515	<0.001

[a]No difference; [b]2nd difference

Table 4. Coefficients of the regression model on *LN*(*REAL-PRICE*) in Europe, 1500–1800. For Constant, EUTemp. and lnPopulation, adjusted R^2: 0.235; test of heteroscedasticity (Breusch-Pagan-Godfrey method): observation 1.097, p = 0.577

	Estimate		*t*	p
	B	SE		
Constant	–1.058	0.200	–5.278	<0.001
EUTemp.	–0.093	0.011	–8.144	<0.001
EUPrecip.	0.012	0.018	0.030	0.653
lnPopulation	–0.165	0.042	–3.892	<0.001

ADF test results, and based on this, the GCA is processed at the same level of differencing. For example, if 2 variables that are both linked can be stationary at zero difference with the least significant level of 0.1, then the GCA will be carried out at zero difference. Table 2 shows the differencing level and the BIC lag for the GCA calculation. The GCA is then implemented and the results are presented in Table 3.

3.2. Regression modeling

In the modeling analysis, both the regression and the ARX are implemented in a linear manner. Thus, the real price and the population are first taken by the logarithm (log) because their growth follows exponential changes. The log transformation stabilizes the variances of these variables (Durbin et al. 2002) and makes them suitable for use in the linear regression (Tsiatis 1990, Smith 1993). In economics and other applied studies, the natural logarithmic transformation is commonly adopted (Koop 2005, Pemberton & Rau 2007); therefore, the real price data and population data are taken as the natural log before implementing the regression and ARX modeling.

Table 4 reports the regression results of the real price of grain, temperature, precipitation and population. Unlike the other variables, precipitation is not significant at the significance level of 0.1. In Table 3, the null hypotheses are rejected at the significance level of 0.1 except between precipitation and the real price of grain. This also suggests that in general precipitation was not a limiting factor to agriculture in Europe but temperatue was (Poulsen 1997), which is consistent with the GCA results. Accordingly, temperature is the restrictive factor in the European agrarian economy. Particularly on a large spatial scale, temperature is a more appropriate indicator of climate change rather than precipitation (Bryson & Murray 1977, Sumner 1988, Jones & Bradley 1992). However, this does not negate the importance of precipitation at a regional or local scale. Temperature has been used to represent climate change in a large-scale study (Zhang et al. 2011a,b). As a result, precipitation is excluded from the ARX modeling based on the statistical results shown in Tables 3 & 4.

The regression of the real price of grain on temperature and population is presented in Table 4 and the test of heteroscedasticity is done by the Breusch–Pagan–Godfrey method. In the table, as the value of the test statistic is 1.097 and the p-value is 0.577, the null hypothesis accepts that the regression does not have heteroscedasticity. As a result, the data series obeys a consistent statistic structure and warrants the use of ARX modeling for further analysis. Moreover, the result of the aforementioned statistical test quantitatively justified several current understandings that there was little change in the technological level in agriculture or economic structure

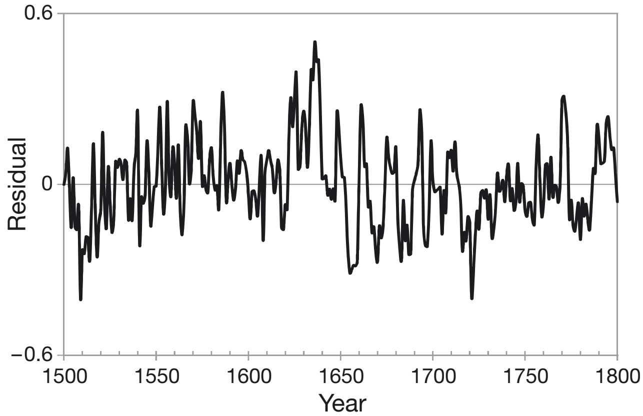

Fig. 1. Residual plot of the regression model based on temperature and population

in pre-industrial Europe (Fussell 1966, Clark 2006, 2007, Zanden 2009).

To assess the regression results further, the residual is always checked because it contains all the remaining information in the regression, as shown in Fig. 1. In statistics, residue plots should be examined when conducting regression analysis. Among various test methods, the autocorrelation function (ACF) and the partial autocorrelation function (PACF) are useful in checking the data series over different periods to summarize properties in the time domain (Harvey 1993). In Fig. 2, the ACF and PACF both show that the residue is auto-correlated. Furthermore, in Fig. 3, the residue has a linear association with past price conditions; it is regarded as price stickiness in economic theory (McCallum 1986, Sbordone 2002). Fig. 3 illustrates the linear pattern between the residues and the price at different time lags, which directly visualize the ACF and PACF results.

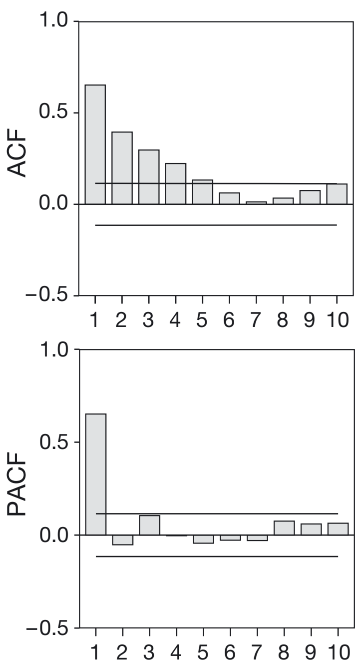

Fig. 2. Autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals of the regression model. Horizontal lines: lag numbers

3.3. ARX modeling

As shown in Fig. 3, the selection of the lag number is problematic in ARX modeling; therefore, forward

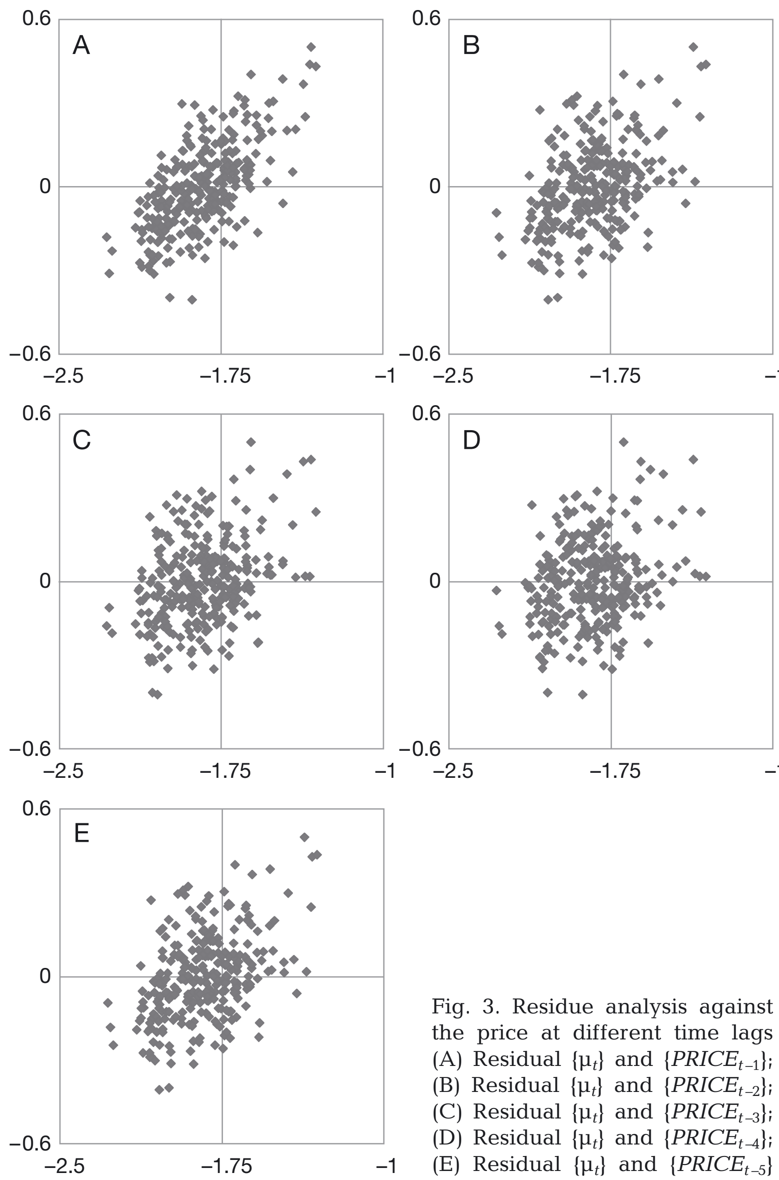

Fig. 3. Residue analysis against the price at different time lags (A) Residual $\{\mu_t\}$ and $\{PRICE_{t-1}\}$; (B) Residual $\{\mu_t\}$ and $\{PRICE_{t-2}\}$; (C) Residual $\{\mu_t\}$ and $\{PRICE_{t-3}\}$; (D) Residual $\{\mu_t\}$ and $\{PRICE_{t-4}\}$; (E) Residual $\{\mu_t\}$ and $\{PRICE_{t-5}\}$

Table 5. Coefficients of the ARX(5) model with time trends

			Estimate	SE	T	p
LnRP	Constant		−30.130	246.628	−0.122	0.903
	AR	Lag 1	0.747	0.060	12.397	<0.001
		Lag 2	−0.211	0.075	−2.812	0.005
		Lag 3	0.122	0.075	1.634	0.103
		Lag 4	−0.007	0.074	−0.096	0.924
		Lag 5	−0.065	0.059	−1.099	0.273
EUTemp.			−0.054	0.010	−5.462	<0.001
LnPopulation			2.182	1.137	1.919	0.056
t			0.019	0.461	0.042	0.967
t^2			1.23×10^{-11}	0.000	4.33×10^{-8}	1.000
t^3			-3.044×10^{-9}	5.82×10^{-8}	−0.052	0.958

Table 6. Coefficients of the ARX(3) model without a constant. Adjusted R^2 for ARX modeling: 0.639

			Estimate	SE	t	p
LnRP	AR	Lag 1	0.860	0.058	14.931	<0.001
		Lag 2	−0.252	0.075	−3.344	0.001
		Lag 3	0.184	0.058	3.186	0.002
EUTemp.			−0.016	0.009	−1.812	0.071
LnPopulation			−0.389	0.006	−64.373	<0.001

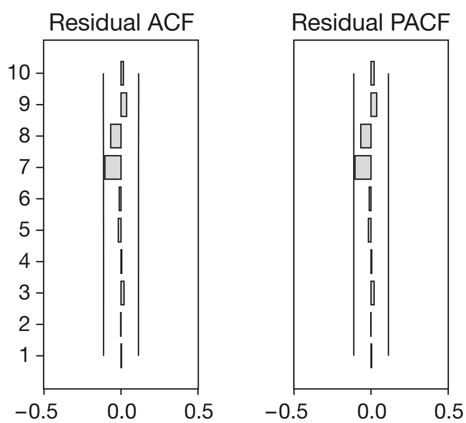

Fig. 4. Residual autocorrelation function (ACF) and partial autocorrelation function (PACF) of the ARX(3) model. Vertical lines: lag numbers

and backward selections are 2 common methods used. Given that our study aims to identify the long-term effect of climate change on the grain market, the backward method of parameter selection can preserve the existing variables that have already been used. Thus, a backward method is adopted in this study. A flexible time trend is also considered in the modeling, as shown in Table 5. It is refined step by step by removing the insignificant variables. To preserve the time trend in the modeling, we first removed ARX(5) to ARX(3) with t, t^2, and t^3. In the second step, we exclude t, t^2, t^3, and the constant, which are still insignificant variables. The final results are presented in Table 6. Based on these results, the ARX(3) model parameters are all significant at the 0.1 level. This model is statistically significant, and it can be used in the analysis. The residual plot was also checked through ACF and PACF, as shown in Fig. 4.

4. DISCUSSION

4.1. Annual effect of climate variations

Annual climate variation has an effect on the price of grain. The statistical model results (Table 6) are consistent with country level findings presented in the literature (see Section 2). The price of grain is closely related to climate. Specifically, mild temperatures lead to lower prices because good harvests can provide sufficient supply to the market. Lower temperatures result in higher prices because of poor production and scarcity in the grain market. If temperature decreases by x, then the price of grain in the market will increase by $e^{0.016x}$ times. In addition, $e^{0.016x}$ is larger than x, that is, the temperature's effect on the grain market is more significant than the temperature fluctuation rate. Furthermore, the simulation shows that the greater the changes in temperature, the larger the changes in price. When $x = 0.2$, the increase in price is more than twice that of when $x = 0.1$. Therefore more change in climate will yield a much greater effect on the grain market, thus further showing the vulnerability of the grain market.

Based on the modeling results, the interaction between climate change and the grain market is not a linear process, although this nonlinear relationship is caused by the modeling design in the research (cf. Section 3.2). However, as pointed out, the process of climate variation can be nonlinear (Rahmstorf 2000, Schneider 2004), and its corresponding effect on the socioeconomic system can also result in nonlinear patterns (Mastrandrea & Schneider 2001, Adger et al. 2009). Therefore, following the research on climate change issues, price and temperature can be considered as exponential functions according to our statistical results and analysis.

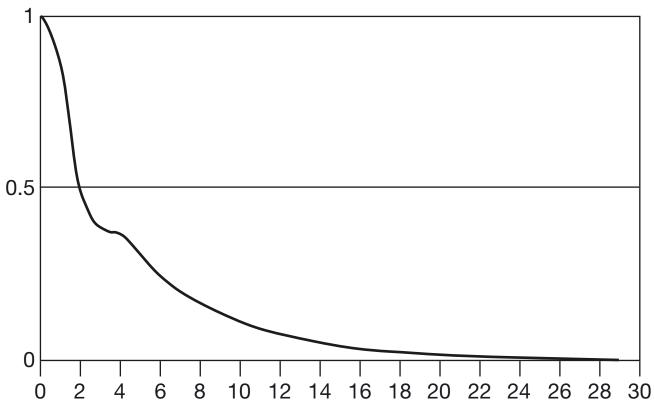

Fig. 5. Decline rate of the temperature effect in the long term

4.2. Lasting effect of climate variation

One of the advantages of the ARX method is that it can be used to evaluate long-term consequences. Based on several studies (Durán et al. 2007, Huusom et al. 2010, Qin et al. 2010), ARX can be transformed statistically to simulate variations at different time scales, depending on the purpose of the study. Accordingly, using the simulated ARX model in this paper, the effect of climate change of year t on the following years $t+j$ (j = 1, 2, 3...) can be identified through mathematical conversion as follows.

To examine the lasting effect of the temperature parameter, the ARX model should be transformed. It is written as the following expression:

$$\phi(B)Y_t = X_t'\beta \quad (9)$$

where X and Y are matrices and $\phi(x) = 1 - 0.86x + 0.252x^2 - 0.184x^3$. The ARX model in Table 6 can be rewritten as:

$$\phi(B)y_t = -0.016x_{t,1} - 0.389x_{t,2} \quad (10)$$

or as

$$\phi(B)y_t = \sum_{j=0}^{\infty}\varphi_j \times (-0.016x_{t-j,1} - 0.389x_{t-j,2}) \quad (11)$$

where B is the backshift operator and

$$\phi_1 = 0.86 \qquad \phi_2 = -0.252 \qquad \phi_3 = 0.184$$

$$\varphi_0^{(0)} = 1 \qquad \varphi_1^{(0)} = 0.86 \qquad \varphi_2^{(0)} = 0.4876$$

$$\varphi_R^{(0)} = 0.86\varphi_{R-1}^{(0)} - 0.252\varphi_{R-2}^{(0)} + 0.184\varphi_{R-3}^{(0)} \quad R \geq 3 \quad (12)$$

Therefore, the attenuation of the temperature effect on the socioeconomic mechanism will last for 25 yr at most, according to Fig. 5, which is based on Eq. (12). After 25 yr, the effect will be almost equal to zero. In the literature, the lasting effect of climate change on society has been noticed in academia step by step (McGeehin & Mirabelli 2001, Lee et al. 2009) though in a limited number of studies. For instance, in imperial China, the maximum war frequencies in the southern part of the country would occur around 20 yr after the start of climate cooling in the long term (Zhang et al. 2007b). In pre-industrial Europe, the social crisis was observed less than 30 yr after the drop in the agrarian economy driven by long-term climate cooling (Zhang et al. 2011b). Although existing studies obtained such findings through qualitative descriptions, their impressions on the time delay in economic and social responses under the impact of climate change matches the modeling results of our study.

4.3. The General Crisis and long-term cooling

In Sections 4.1 and 4.2, we assessed the short- and long-term effects of climate variations through the ARX modeling results, and provide an explanation for the European General Crisis between 1590 and 1660 AD (see Section 1). In Fig. 6, the shaded area representing the General Crisis is characterized by low temperature. A closer examination of this period shows that the temperature pattern is anomalous in 2 respects: (1) the temperature was at its lowest level during the entire study period from 1500 to 1800 AD; (2) the period of low temperature lasted for >30 yr, which is regarded as climate change (see Section 1). This aspect makes that particular time period different from other periods that also experienced low temperatures, such as the periods 1690 to 1700 AD and 1730 to 1740 AD.

The model can thus be used to explain the cause of the economic crisis in the grain market during the 17th century in a step-by-step manner. To supplement our quantitative results, Fig 7 presents temperature and price together, with raw data in Fig. 7A, and the data low-pass smoothed by the Butterworth Filter (to more clearly visualize their association) in Fig. 7B. Based on Fig. 7 and our ARX modeling results, the findings are as follows:

(i) Low temperature leads to high price on an annual scale, which is corroborated in this study by the ARX modeling results (cf. Section 4.1). The low temperatures during the 17th century increased the price of grain and raised the basic price level of grain in the market due to economic stickiness.

(ii) The effect of temperature fluctuations in year t will last for 25 yr at most based on the modeling results. The effects of temperature events occuring shortly before the timepoint in question and continuing up to this point could add up to affect the price

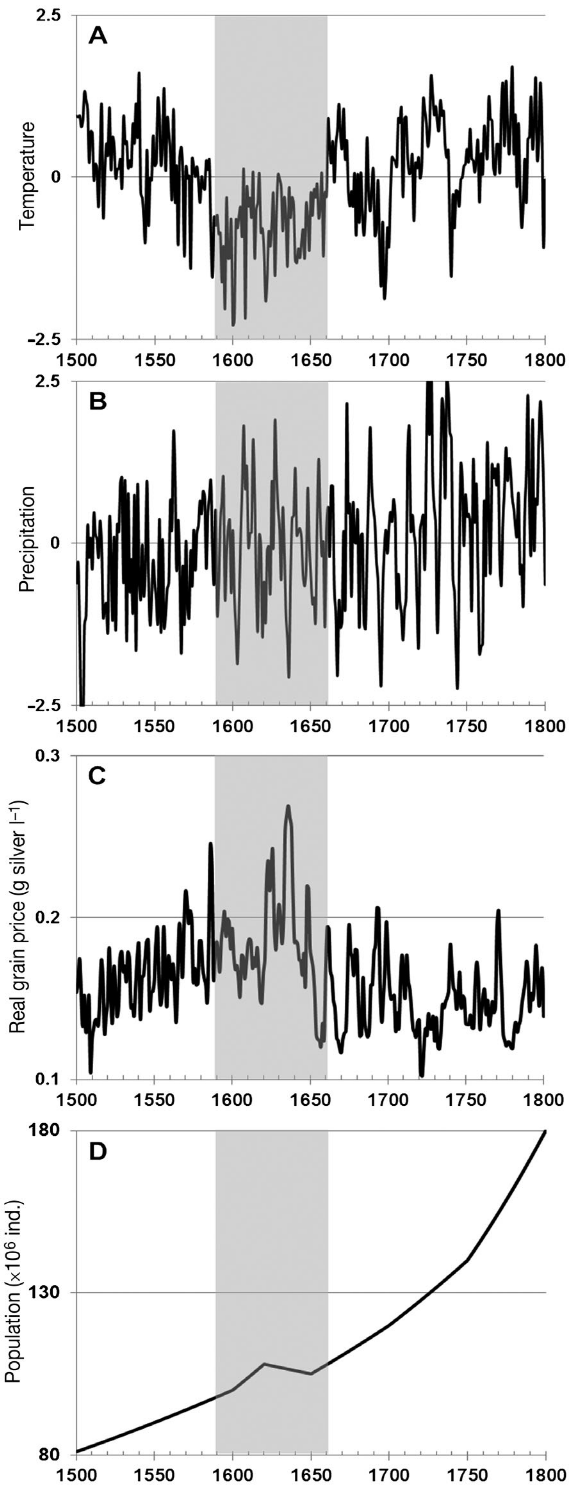

Fig. 6. Temperature, Precipitation, Real Price of Grain, and Population in Europe, 1500–1800. Notes: (A) Normalized temperature change records in Europe, (B) Normalized precipitation change records in Europe, (C) European real price of grain with a base year of 1500, and (D) European population size. Shaded area: cold phase from 1590 to 1660 AD, which contemporary historians refer to as the General Crisis of the 17th Century

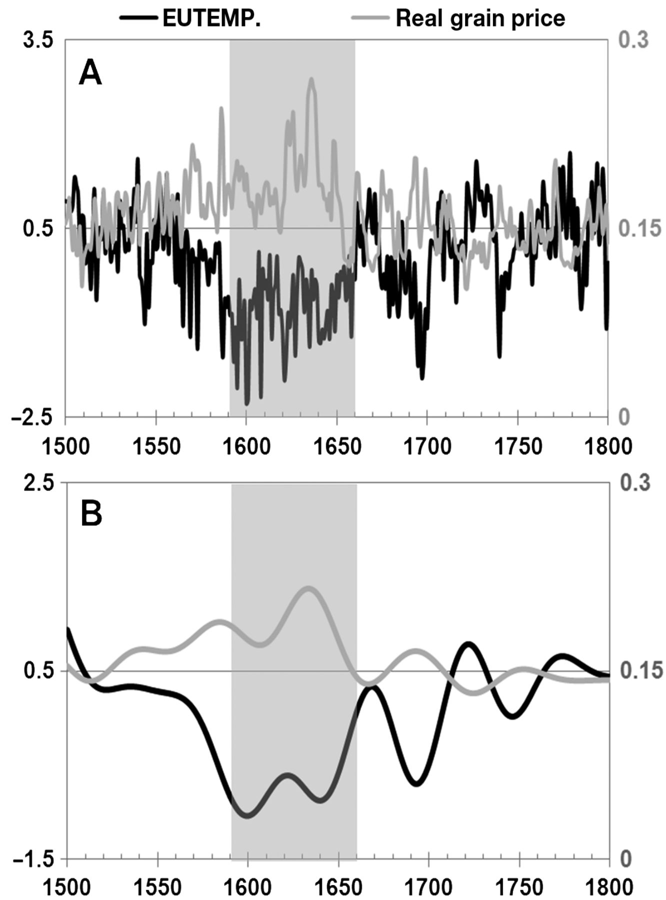

Fig. 7. Temperature and real price of grain fluctuations from 1500–1800 AD. (A) The series in raw data format. (B) The data series is smoothed by a low-pass Butterworth filter of 40 years. The shaded area represents the cold phase from 1590 to 1660 AD, which contemporary historians refer to as the General Crisis of the 17th Century

in the grain market. Theoretically, the cooling temperature could disturb the economy by its cumulative effect if it continues over a long period. When climate cooling lasts >25 yr, the economy is likely to deteriorate because of the cumulative effects of low temperatures. In consequence, the grain prices rise to abnormally high levels and economic crisis occurs.

Empirical data over the study period help us understand the results of the statistical modeling, and thus to better understand the causes of the 17th-century crisis. The empirical data series in Fig. 7 shows that the sustained cold period from 1590 to 1660 AD was followed by a markedly increased grain price in the second half of that period. The results of the ARX modeling with this observation could explain why the lowest temperatures recorded began in the 1600s, but the peak of grain prices occurred in the 1630s with an almost 30 yr lag (Fig. 7).

The continuing high prices from 1590 to 1660 AD, especially the extremely high price of grain in the 1630s, are regarded as the foundation for the economic crisis in pre-industrial Europe. These findings and understandings gained from the economic crisis in the 17th –century can also explain why the cold period that occurred in the 1700s and the 1740s only slightly increased the price of grain in the market, but did not result in an economic crisis — the low temperatures during these two periods did not last for more than 10 yr; therefore, there was not sufficient accumulated stress to cause a rapid increase in price .

The effect of climate variation on the past agrarian economy occurred at both short and long timescales. The long-term effect of climate variation lasts for 25 yr at most (see above, this section, and Section 4.2). With the combination of the empirical data on the agrarian economy during the study period, in the short-term, low temperatures only increase the price of grain and do not necessarily lead to severe economic problems. However, climate change (a long-term climate variation) could ultimately lead to economic crisis. As a result of economic crisis resulting from extremely high grain prices, a peak of human suffering — including famine, war, social disturbances, malnutrition — also occurred in the 1630s, and these are factors which can directly trigger social catastrophes (Zhang et al. 2011b).

If cooling trends last for a long period of time, similar to the 17th century economic crisis, the cumulative climatic effect could eventually damage economic equilibrium. Long-term climate change could have an even more disastrous effect on society (Symons 1979, Campbell 2000, Zhang et al. 2011b). In the long run, institutional and social buffering mechanisms would be exhausted because of recurrent subsistence crises caused by long-term cooling (Orlove 2005). Other studies of the 17th-century crisis have improved our understanding of sociopolitical and demographic factors (Goldstone 1991, Fischer 1996) and class struggle (Hobsbawm 1954). In contrast, the present study presents a perspective on the quantitative interpretation of the 17th century economic crisis based on ARX modeling.

As shown in Fig. 6, the population of Europe dropped dramatically during the 1630s. Numerous studies have attempted to explain this phenomenon during this period, foremost of which is climate-induced theory (Utterström 1955, Galloway 1985, 1994, Zhang et al. 2007a). Detailed explanation of changes in population is beyond the scope of this study, but some basic points can be mentioned. The population mainly served as the producer rather than the consumer, which affected agricultural production during the study period (Zhang et al. 2011b). The role of the population as producer exceeds the consumption of the population as the consumer which can also be supported from the ARX modeling results. The decrease in population also led to a smaller labor pool in the agricultural sector, thus also affecting agricultural production. Market supply therefore decreased as a result.

5. CONCLUSIONS

Climate change played a crucial role in the European agrarian economy during the pre-industrial era. Our study is the first attempt to use ARX modeling in investigating the relationship between climate and the economy in agrarian Europe, specifically from 1500 to 1800 AD. This study fills the gap in previous quantitative analyses on the short- and long-term effects of climate variations on past agrarian economies. Based on the modeling results, it also compares the consequences of climate variation on an agrarian economy in the short-term, and climate change (long-term climate variation) in pre-industrial Europe. By demonstrating such an impact, the results of our study provide a new perspective on the economic crisis of the 17th century.

According to statistical analysis, temperature had a relatively greater significant effect on grain prices than precipitation in pre-industrial Europe on a large spatial scale. In the short-term, a cooler climate can lead to high prices because of poor production and supply scarcity in the grain market. Larger changes in temperature can lead to relatively larger price changes, indicating the nonlinear interaction between climatic conditions and past economies. In the long-term, the effect of climate variations after the event itself can last for approximately 25 yr at most. If climate variations are lengthy in an agrarian society (≥25 yr) the climatic effect can accumulate over time and eventually result in an economic crisis. In brief, short-period climate variation merely raises prices, while actual climate change results in economic crisis. The study detected the short- and long-term impacts of climate variations on society during Europe's pre-industrial era. Furthermore, it clearly compared the consequences of climate variation (short-term) and climate change (long-term). Therefore, methodological thinking with different temporal scales needs more scholarly attention in the future.

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