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CLIMATIC FLUCTUATIONS AND THE DIFFUSION OF AGRICULTURE

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ABSTRACT

This research examines variations in the diffusion of agriculture across countries and archaeological sites. The theory suggests that a society's history of climatic shocks shaped the timing of its adoption of farming. Specifically, as long as climatic disturbances did not lead to a collapse of the underlying resource base, the rate at which foragers were climatically propelled to experiment with their habitats determined the accumulation of tacit knowledge complementary to farming. Thus, differences in climatic volatility across hunter-gatherer societies gave rise to the observed spatial variation in the timing of the adoption of agriculture. Consistent with the proposed hypothesis, the empirical investigation demonstrates that, conditional on biogeographic endowments, climatic volatility has a non-monotonic effect on the timing of the adoption of agriculture. Farming diffused earlier across regions characterized by intermediate levels of climatic fluctuations, with those subjected to either too high or too low intertemporal variability transiting later.

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1 Introduction

The impact of the transition from hunting and gathering to agriculture on the long-run socioeconomic transformation of mankind is perhaps only comparable to that of the Industrial Revolution. Hunting and gathering, a mode of subsistence that entails the collection of wild plants and the hunting of wild animals, prevailed through most of human history. The prehistoric transition from foraging to farming has been referred to as the Neolithic Revolution, a term that captures both the general period in history when the transition took place and the profound socioeconomic changes associated with it.

This research theoretically and empirically examines the diffusion of agriculture. It advances and tests the hypothesis that a society's history of climatic fluctuations determined the timing of its adoption of farming. The theory suggests that climatic volatility induced foragers to intensify their subsistence activities and expand their dietary spectrum. To the extent that climatic shocks did not eliminate the underlying subsistence resource base, societies that were frequently propelled to exploit their habitats accumulated tacit knowledge complementary to agricultural practices, thereby facilitating the adoption of farming when the technology diffused from the Neolithic frontier. In contrast, extremely volatile or stationary environments were less conducive to the adoption of agriculture. At one end, societies facing static climatic conditions were not sufficiently coerced to take advantage of their habitats. At the other end, extreme climatic shocks (e.g., a return to semi-glacial or arid conditions) prevented the type of ecological experimentation instrumental for the accumulation of knowledge complementary to farming.

The current approach weaves together two distinct influential theories from the archaeological literature regarding the onset of agriculture in the Near East, namely the "Broad Spectrum Revolution" and the "climate change" hypotheses. According to the "Broad Spectrum Revolution" argument, pioneered by Binford (1968) and Flannery (1973), exogenous population growth instigated the exploitation of new species, leading to the deliberate cultivation of certain plants, especially wild cereals, and setting the stage for their domestication (see Weiss et al., 2004, for recently uncovered evidence). On the other hand, proponents of the "climate change" hypothesis, including Byrne (1987), Bar-Yosef and Belfer-Cohen (1989), and Richerson, Boyd and Bettinger (2001), highlight how the advent of agriculture took place as a result of unusual climatic changes in the early Holocene.

Motivated by these two prominent insights, the proposed theory links climatic variability with the more efficient exploitation of existing resources and the inclusion of previously unexploited species into the dietary spectrum. It illustrates the importance of climatic shocks in transforming foraging activities and augmenting societal practices complementary to the adoption of agriculture (expansion of tool assemblages, more intense habitat-clearing and plant-interventionist operations, etc.). The study thus identifies the spatial heterogeneity of regional climatic sequences as a fundamental source of the differential timing of the adoption of farming across regions.

The predictions of the theory are tested using cross-sectional data on the timing of the adoption of agriculture. Consistent with the theory, the results demonstrate a highly statistically significant and robust hump-shaped relationship between the intertemporal standard deviation of temperature and the timing of the Neolithic Revolution. Specifically, the analysis exploits cross-country variation in temperature volatility to explain the variation in the timing of the agricultural transition across countries. Due to the unavailability of worldwide prehistoric temperature data, the analysis employs highly spatially disaggregated monthly time-series data between 1901 and 2000 to construct country-level measures of the mean and standard deviation of temperature over the course of the last century. The interpretation of the empirical results is thus based on the identifying assumption that the cross-regional distribution of temperature volatility during the 20th century was not significantly different from that which existed prior to the Neolithic Revolution. While this may appear to be a somewhat strong assumption, it is important to note that the spatial distribution of climatic factors is determined in large part by spatial differences in microgeographic characteristics, which remain fairly stationary within a given geological epoch, rather than by global temporal events (e.g., an ice age) that predominantly affect the worldwide temporal distribution of climate. Nevertheless, to partially relax the identifying assumption, the analysis additionally employs a volatility measure constructed from new time-series data on historical temperature over the 1500–1900 time period (albeit for a smaller set of countries), uncovering findings that are qualitatively similar to those revealed using temperature volatility over the course of the last century.

Arguably, the ideal unit of analysis for examining the relationship between climatic endowments and the diffusion of farming would be at the human-settlement level rather than the country level. It is precisely along this dimension that the empirical investigation is augmented. Specifically, the analysis employs data on the timing of Neolithic settlements in Europe and the Middle East to explore the role of local, site-specific climatic sequences in shaping the adoption of farming across reliably excavated and dated archaeological sites. Consistent with the predictions of the theory, and in line with the pattern uncovered by the cross-country analysis, Neolithic sites endowed with moderate climatic volatility are found to have transited earlier into agriculture. The recurrent finding that climatic volatility has had a non-monotonic impact on the adoption of farming, across countries and archaeological sites alike, sheds new light on the climatic origins of the Neolithic Revolution.[1]

In revealing the climatic origins of the adoption of agriculture, this research contributes to a vibrant body of work within economics that has explored the deeply-rooted determinants of comparative economic development (see Spolaore and Wacziarg, 2013, for an excellent review of this literature). Specifically, Diamond (1997) emphasizes that the transition to agriculture led to the rise of civilizations and conferred a developmental head-start to early agriculturalists, via the rapid development of written language, science, military technologies, and statehood. In line with this argument, Olsson and Hibbs (2005) show that geography and biogeography may, in part, predict contemporary levels of economic development through the timing of the transition to agriculture, whereas Ashraf and Galor (2011) establish the Malthusian link from technological advancement to population growth, demonstrating the explanatory power of the timing of the Neolithic Revolution for population density in pre-industrial societies.[2] Moreover, Galor and Moav (2002, 2007) and Galor and Michalopoulos (2012) argue that the Neolithic Revolution triggered an evolutionary process that affected comparative development, whereas Comin, Easterly and Gong (2010) find that historical technology adoption, largely shaped by the timing of the transition to agriculture, has a significant impact on contemporary economic performance.

By investigating the interplay between climatic fluctuations and technological evolution in the very long run, this study also contributes to a growing body of theoretical and empirical work regarding the relationships between economic growth, technical change, and the environment (e.g., Acemoglu et al., 2012; Dell, Jones and Olken, 2012; Peretto, 2012).

[1] The distribution of contemporary hunter-gatherer societies is also in line with the proposed theory. Hunter-gatherers today are typically found either in areas characterized by extreme climatic conditions, like the poles and deserts, or in rich coastal regions that possess little climatic variation (see, e.g., Keeley, 1995).

[2] Interestingly, using both cross-country and cross-archeological-site data (as in the current study), Olsson and Paik (2012) provide new evidence, showing that within the Western agricultural core (i.e., Southwest Asia, Europe, and North Africa), there is a negative association between the onset of farming and contemporary economic and institutional development.

The rest of the paper is organized as follows. Section 2 briefly reviews the economic literature on the origins of agriculture. Section 3 lays out the conceptual framework, followed by a simple model of climatic shocks and the adoption of agriculture. Section 4 discusses the empirical findings from the cross-country and cross-archaeological-site analyses, and, finally, Section 5 concludes.

2 Related Literature

The Neolithic Revolution has been a long-standing subject of active research among archaeologists, historians, and anthropologists, recently receiving increasing attention from economists. The focus of this study is on the role of climatic shocks in the *adoption* of farming. Nevertheless, the historical and archaeological record on instances of *pristine* agricultural transitions also emphasizes the role of climatic changes in transforming hunter-gatherer activities (see Ashraf and Michalopoulos, 2011, for a detailed summary of complementary research findings among archaeologists, paleoclimatologists, and ethnographers). The brief review below is hardly meant to be exhaustive, and it is mostly indicative of hypotheses advanced by economists with respect to pristine agricultural transitions (see Pryor, 1983, and Weisdorf, 2005, for surveys).

Early work by Smith (1975) examines the overkill hypothesis, whereby the Pleistocene extinction of large mammals, as a consequence of excessive hunting, led to the rise of agriculture. In pioneering the institutional view, North and Thomas (1977) argue that population pressure, coupled with the shift from common to exclusive communal property rights, sufficiently altered rational incentive structures to foster technological progress with regard to domestication and cultivation techniques. Moreover, Locay (1989) suggests that population growth, due to excessive hunting, resulted in smaller land-holdings per household, thereby inducing a more sedentary lifestyle and favoring farming over foraging.

More recently, Marceau and Myers (2006) provide a model of coalition formation where, at low levels of technology, a grand coalition of foragers prevents the over-exploitation of resources. Once technology reaches a critical level, however, the cooperative structure breaks down and ultimately leads to a food crisis that paves the way to agriculture. Focusing on the spread of farming, Rowthorn and Seabright (2010) argue that early farmers had to invest in defense due to imperfect property rights, thus lowering the standard of living for incipient agriculturalists.[3] In other work, Weisdorf (2003) proposes that the emergence of non-food specialists played a critical role in the transition to agriculture, while Olsson (2001) theoretically revives Diamond's (1997) argument that regional geographic and biogeographic endowments, with respect to the availability of domesticable species, made agriculture feasible only in certain parts of the world.

Finally, Baker (2008) develops and estimates a model of the transition to agriculture using cross-cultural data on the incidence of farming, finding that cultures located farther from pristine centers of agricultural transition experienced a later onset of farming. The empirical analysis in this study establishes a similar pattern wherein distance to the closest Neolithic frontier has a negative impact on the timing of the transition to agriculture, both across countries and across archaeological sites. The current study is also complementary to recent work by Dow, Olewiler and Reed (2009) that examines the onset of the Neolithic Revolution in the Near East. According to their analysis, a single abrupt climatic reversal forced migration into a few ecologically favorable sites, thereby making agriculture more attractive in these locales.

[3] Relatedly, some studies in the economics literature on pristine transitions (e.g., Weisdorf, 2009; Robson, 2010) have focused on attempting to explain the puzzle of the emergence of farming, given that early agriculturalists are known to have been worse-off than their hunter-gatherer predecessors (Cohen, 1977). While interesting, this problem is not germane to the current analysis as it does not pertain to heterogeneity across societies in the timing of the adoption of agriculture.

3 The Proposed Theory

3.1 Conceptual Framework

Before presenting the model, it is useful to briefly review the main elements of the proposed theory and their interplay in transforming the hunter-gatherer regime. As illustrated in Figure 1, moderate climatic shocks increase the risk of acquiring existing resources for subsistence. As a result, hunter-gatherers are forced to experiment with novel food-extraction and processing techniques, thus altering their resource acquisition patterns and incorporating previously unexploited species into their diet. Such transformations in subsistence activities may be manifested as increased investments in tool making, more intense habitat-clearing and plant-management practices, or the development of a more sedentary infrastructure.

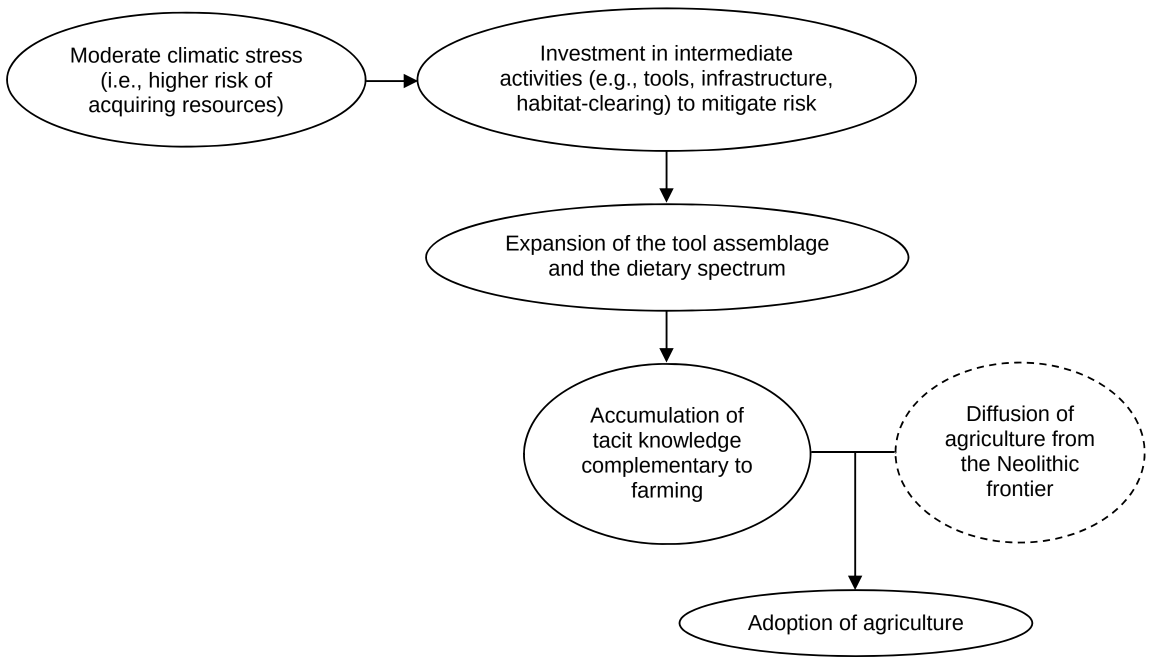


Figure 1: The Main Elements of the Proposed Theory

The aforementioned transformations permanently enhance society's knowledge with respect to the collection and processing of a broad spectrum of resources. This is a novel channel for recurrent climatic shocks to gradually increase the set of foraging activities. The main mechanism for the adoption of agriculture is that, given a sequence of non-extreme climatic shocks, the knowledge accumulated from exploiting an ever broader spectrum of resources is complementary to agricultural techniques. Hence, societies endowed with a history of moderate climatic fluctuations are more likely to adopt farming, once the agricultural technology arrives from the Neolithic frontier.

3.2 A Simple Model of Climatic Shocks and the Adoption of Agriculture

Consider a simple hunter-gatherer economy where activities extend over infinite discrete time, indexed by $t = 0, 1, 2, \ldots \infty$. In each period, the economy produces a single homogeneous final good (food), using a production technology that combines labor with a continuum of intermediate input varieties. These intermediate input varieties may be interpreted broadly as different types of tools and techniques that enable the extraction of different subsistence resources (plant and animal species). Land is not a scarce factor of production in this primitive stage of development, so the quantity of food produced is constrained only by the availability of labor, the breadth of the dietary spectrum, and the intensity with which each subsistence resource is exploited. In every period, individuals are endowed with one unit of time, and the size of the labor force remains constant over time.[4]

Consider first how food gets produced in this foraging economy when it is climatically unperturbed. Final output at time t, Y_t, in such an environment is given by:

$$Y_t = \left[\int_0^{N_t} X_{i,t}^{1-\alpha} \, di \right] L^{\alpha},$$

where $\alpha \in (0,1)$; $L > 0$ is the (fixed) size of the labor force; $X_{i,t}$ is the amount of intermediate good (the type of tool, for instance) used to acquire resource i at time t; and N_t is the total number of intermediate input varieties, and thus the total number of different resources that foragers can extract, at time t. $N_0 > 0$ is given, and N_t stays constant over time as long as the environment remains climatically static. As will become apparent, however, N_t will grow endogenously over time in a climatically dynamic environment, where foragers are forced to experiment with their habitat in order to partially counteract the detrimental effects of climatic shocks on output. Food is non-storable, so the amount produced in any given period is fully consumed in the same period.

Given a climatically static environment, the gross quantity of food per hunter-gatherer at time t is:

$$y_t = \int_0^{N_t} x_{i,t}^{1-\alpha} \, di,$$

where $y_t \equiv Y_t/L$; and $x_{i,t} \equiv X_{i,t}/L$.

Intermediate inputs fully depreciate every period, and given the primitive nature of the economy, there are no property rights defined over either these inputs or the knowledge required to create and apply them. Once the know-how for creating and applying a new intermediate input (that allows the processing of a new resource) becomes available, anyone in society can produce one unit of that input at a marginal cost of $\mu > 0$ units of food. Hence, the quantity of food per hunter-gatherer at time t, net of the cost of producing intermediate inputs, is:

$$\tilde{y}_t = \int_0^{N_t} x_{i,t}^{1-\alpha} \, di - \int_0^{N_t} \mu x_{i,t} \, di.$$

Maximization of net food per forager implies that the quantity demanded of the intermediate input used to acquire resource i at time t, $x_{i,t}$, will be the same across the different resource varieties at time t. Specifically,

$$x_{i,t} = \bar{x} \equiv \left[\frac{1-\alpha}{\mu} \right]^{\frac{1}{\alpha}}.$$

[4] The assumptions regarding the non-scarcity of land as a productive factor and constant population size imply that the current model does not admit a long-run Malthusian equilibrium. These abstractions permit the setup to focus on highlighting the role of climatic volatility in determining the timing of the adoption of agriculture. Incorporating Malthusian considerations does not qualitatively alter the key theoretical predictions. See Ashraf and Michalopoulos (2011).

Thus, in equilibrium, the gross and net quantities of food per hunter-gatherer at time t will be:

$$\begin{aligned} y_t &= N_t \bar{x}^{1-\alpha}; \\ \tilde{y}_t &= N_t \bar{x}^{1-\alpha} - N_t \mu \bar{x} = \alpha N_t \bar{x}^{1-\alpha}. \end{aligned}$$

Intuitively, in any given period, the amount of (gross or net) food per forager will be directly proportional to (i) the breadth of the hunter-gatherer dietary spectrum, as reflected in the total number of intermediate input varieties; and (ii) the intensity with which each species is exploited, as reflected in the quantity of the intermediate input used to acquire and process the resource. Furthermore, net output reflects the proportion α of gross output that accrues to labor as food, once the costly production of intermediate inputs has been taken into account.

Suppose now that the environment at time t is affected by a deviation of a climatic characteristic (such as temperature) from its long-run intertemporal mean.[5] Food production now becomes subject to an "erosion effect" due to adverse changes in the subsistence resource base, resulting from this perturbation to the environment.[6] Specifically, net food per forager is now given by:

$$\tilde{y}_t = [1 - \epsilon_t] \int_0^{N_t} x_{i,t}^{1-\alpha} \, di - \int_0^{N_t} \mu x_{i,t} \, di,$$

where $\epsilon_t \in [0, 1)$ is the size of the erosion at time t. Note that the erosion will reduce food per hunter-gatherer both directly and indirectly. The indirect effect arises from the fact that, taking ϵ_t as given, the lower marginal productivity of the intermediate inputs (tools) results in lower quantities of these inputs being used for resource acquisition. In particular, the quantity demanded of the intermediate input used to acquire resource i at time t, $x_{i,t}$, will now be:

$$x_{i,t} = \hat{x}(\epsilon_t) = \left[\frac{[1 - \alpha] \times [1 - \epsilon_t]}{\mu} \right]^{\frac{1}{\alpha}}.$$

The erosion of final output, however, can be mitigated by the reallocation of time (or labor) from food production to experimentation (R&D activities), in an attempt to partially counteract the overall decline in resource abundance. Specifically,

$$\epsilon_t = \epsilon(e_t, \gamma_t),$$

where $e_t \geq 0$ is the size of the climatic shock; and $\gamma_t \in [0, 1)$ is the fraction of time spent on (or, equivalently, the fraction of the labor force devoted to) experimentation. In addition, for $e_t \in [0, \bar{e})$, $\epsilon(0, \gamma_t) = 0$, $\epsilon_e > 0$, $\epsilon_{ee} < 0$, $\epsilon_\gamma < 0$, $\epsilon_{\gamma\gamma} > 0$, and $\epsilon_{\gamma e} < 0$. For $e_t \geq \bar{e}$, however, $\epsilon(e_t, \gamma_t) = \bar{\epsilon} > 0$. In words, there is no erosion in absence of a climatic shock, and for shocks larger than $\bar{e}$ (that represent, say, a reversion to extreme climatic conditions), the size of the erosion is constant at a high level, $\bar{\epsilon}$. For moderate shocks (i.e., deviations smaller

[5] Since the current setup is intended to exclusively highlight the effect of climatic shocks, it abstracts from the role of average climatic conditions in determining the timing of the adoption of agriculture. Nevertheless, this possibility is explicitly accounted for in the empirical analysis.

[6] Note that both positive and negative deviations in climatic conditions, like increases or decreases in temperature, may have an adverse impact on the subsistence resource base. This is consistent with the notion that each species in nature thrives under specific climatic conditions, and thus, a deviation from this "optimum" decreases its abundance.

than $\bar{e}$), the erosion increases in the size of the climatic shock at a diminishing rate, and it decreases in the allocation of labor to experimentation at a diminishing rate. Moreover, as long as climatic shocks are not extreme, their eroding impact on output can be mitigated by raising the degree of experimentation.

Thus, under a moderate climatic shock, the equilibrium allocation of labor (between food production and experimentation) will be determined by the trade-off between (i) the benefit of having foragers experiment with new methods of exploiting existing resources, in an effort to overcome the erosion effect; and (ii) the cost of lowering output by diverting hunter-gatherers from food acquisition. Specifically, for $e_t \in [0, \bar{e})$, the allocation of labor will be chosen to maximize net food per forager, $[1-\gamma_t]\tilde{y}_t$, given the optimal quantity demanded of each intermediate input, $\hat{x}(\epsilon(e_t, \gamma_t))$. Formally,

$$\gamma_t = \underset{\gamma_t}{\text{argmax}}\ [1-\gamma_t]\left[[1-\epsilon(e_t,\gamma_t)]\int_0^{N_t} x_{i,t}^{1-\alpha}\ di - \int_0^{N_t} \mu x_{i,t}\ di\right]\Bigg|_{x_{i,t}=\hat{x}(\epsilon(e_t,\gamma_t))}.$$

The first-order condition for this problem simplifies to:

$$F(e_t,\gamma_t) \equiv [1-\gamma_t]\epsilon_\gamma(e_t,\gamma_t) + \alpha[1-\epsilon(e_t,\gamma_t)] = 0.$$

Given the specified properties of $\epsilon(e_t, \gamma_t)$, the partial derivative of this condition with respect to γ_t is positive. In particular,

$$F_\gamma(e_t,\gamma_t) = [1-\gamma_t]\epsilon_{\gamma\gamma}(e_t,\gamma_t) - [1+\alpha]\epsilon_\gamma(e_t,\gamma_t) > 0,$$

which ensures the existence of a unique solution to the labor-allocation problem (via the implicit function theorem) for a given e_t,

$$\gamma_t = \gamma(e_t).$$

Moreover, the partial derivative of the first-order condition with respect to e_t is negative,

$$F_e(e_t,\gamma_t) = [1-\gamma_t]\epsilon_{\gamma e}(e_t,\gamma_t) - \alpha\epsilon_e(e_t,\gamma_t) < 0,$$

which, together with $F_\gamma(e_t, \gamma_t) > 0$, implies that the effect of e_t on γ_t, $\gamma'(e_t)$, is positive. Hence, for non-extreme climatic shocks, an increase in the size of the shock will increase the allocation of labor towards experimentation, in an effort to temporarily improve the effectiveness with which resources currently incorporated into the diet (and that are now more scarce in supply) are acquired. Note, however, that there will be no incentive to engage in experimentation either in the absence of a climatic shock (i.e., when $e_t = 0$) or when the deviation is too large (i.e., if $e_t \geq \bar{e}$). Specifically, $\gamma(0) = 0$ and $\gamma(e_t)|_{e_t \geq \bar{e}} = 0$.

The analysis now turns to characterize the evolution of the total number of intermediate input varieties (and thus the expansion of the hunter-gatherer dietary spectrum) over time. To this end, suppose that the contemporaneous effort to mitigate climatic risk via experimentation results in intertemporal knowledge spillovers for the development of new varieties of intermediate inputs that facilitate access to new species.[7] Intuitively, experimentation by hunter-gatherers to improve the productivity of their current toolkit inadvertently generates some technical knowledge for the creation of production methods (new tool

[7] Note that the current setup does not permit experimentation to permanently increase the efficiency with which existing resources are extracted. Allowing the contemporaneous R&D effort to permanently lower the cost of producing intermediate inputs, μ, does not qualitatively alter the main theoretical predictions.

varieties) that can be used to incorporate previously unexploited resources into the dietary spectrum. To help fix ideas, suppose that the extent of these spillovers is proportional to the current labor allocation to experimentation. That is,

$$\Delta N_t \equiv N_{t+1} - N_t = \eta\gamma(e_t)L,$$

where $\eta > 0$. Hence, non-extreme climatic shocks confer permanent "rachet effects" on the breadth of the dietary spectrum over time – a climatic deviation at time t will result in a permanent increase in the number of species exploited from time $t + 1$ onward even if the shock is transitory, in the sense that it dissipates completely by time $t + 1$.

At this stage, the model can be easily applied to link the cross-sectional distribution of the breadth of the dietary spectrum at a point in time with the cross-sectional distribution of climatic history up to that point. Specifically, consider three societies, A, B, and C, at some arbitrary time $T > 0$, and suppose that they have identical initial conditions (specifically, with respect to the initial number of species exploited, N_0) but that they differ in their historical sequences of climatic shocks, $\{e_t^i\}_{t=0}^T$, $i \in \{A, B, C\}$. In particular, for all $t \leq T$, $\bar{e} > e_t^B > e_t^A = 0$, and for some $t \leq T - 1$, $e_t^C > \bar{e} > e_t^B$, with $e_t^C = e_t^B$ for all other t. That is, A has had a climatically static environment, B a history of strictly moderate climatic shocks, and C a climatic history similar to B, except for at least one period when the deviation in C temporarily resulted in extreme climatic conditions. Then, in light of the aforementioned rachet effect associated with non-extreme climatic deviations, it follows that $N_T^B > N_T^C > N_T^A = N_0$. Hence, the number of intermediate input varieties (and, correspondingly, the breadth of the dietary spectrum) at time T will be largest in the hunter-gatherer society with the history of strictly moderate climatic shocks.

The final step of the argument involves relating the above result to the differential timing of the adoption of agriculture. To illustrate this link in a parsimonious manner, suppose that in every period, the model foraging economy has the opportunity to costlessly adopt an agricultural production technology from the world technological frontier. Food production using this alternative technology is:

$$Y_t = A(N_t|\bar{A})L,$$

where $A(N_t|\bar{A})$ is the level of agricultural productivity. Specifically, agricultural productivity depends on how tacit ecological knowledge accumulated by the recipient hunter-gatherer society, and manifested in the breadth of its dietary spectrum, N_t, compares with the level of knowledge necessary for the adoption of farming, $\bar{A} > 0$. When the agricultural technology diffuses across space, the hunter-gatherer society that has been climatically propelled to modify its food acquisition practices by incorporating a broad set of resources in its diet is more likely to have the appropriate know-how for successfully implementing the arriving innovation. A simple formulation of this argument is given by:

$$A(N_t|\bar{A}) = A \times \min\{1, N_t/\bar{A}\},$$

where $A > 0$ is sufficiently large to ensure that if $N_t \geq \bar{A}$, agricultural output will be larger than hunter-gatherer output net of tool costs, thus resulting in the immediate and permanent adoption of farming. If $N_t < \bar{A}$, however, the likelihood that agriculture would be adopted in the current period will be lower the smaller is N_t relative to $\bar{A}$. While a broader hunter-gatherer dietary spectrum makes farming more appropriate for adoption in the present formulation, it may admittedly also be associated with increased specialization in foraging, thus making the adoption of farming less likely. As will become apparent, however, the empirical results suggest that the quantitatively dominant channel is the one where a broader spectrum of resource exploitation favors the adoption of agriculture over further hunter-gatherer specialization. In other words, had the increased-specialization channel been the dominant one, the reduced-form effect of climatic volatility on the timing of the adoption of agriculture would not be hump-shaped.

Consider now the earlier thought experiment with societies A, B, and C. In light of the setup for the adoption of agriculture discussed above, the likelihood that agriculture will have been adopted by time T will be higher in the society with the history of non-extreme climatic shocks (i.e., society B) than either the society with the history of climatic stagnation (i.e., society A) or the society with historical episodes of extreme climatic disturbances (i.e., society C). This reduced-form prediction of the model regarding the non-monotonic (hump-shaped) effect of intertemporal climatic volatility on the timing of the adoption of agriculture is explored empirically in the subsequent section.

4 Empirical Evidence

4.1 Cross-Country Analysis

This section provides empirical evidence consistent with the proposed theory, demonstrating a statistically significant and robust hump-shaped relationship between measures of the intertemporal standard deviation of temperature and the timing of the Neolithic Revolution across countries. Specifically, the analysis exploits cross-country variation in temperature volatility as well as in other geographic determinants, such as mean temperature, distance to the closest Neolithic frontier (i.e., one of seven localities around the world that experienced a *pristine* agricultural transition), absolute latitude, land area, topographic conditions, and biogeographic endowments, to explain the cross-country variation in the timing of the Neolithic Revolution. Due to the unavailability of worldwide prehistoric temperature data, however, the analysis employs highly spatially disaggregated monthly time-series data between 1901 and 2000 to construct country-level measures of the intertemporal mean and standard deviation of temperature over the last century.

The monthly time-series data on temperature, 1901–2000, are obtained from the Climate Research Unit's CRU TS 2.0 data set, compiled by Mitchell et al. (2004). This data set employs reports from climate stations across the globe, providing 1,200 monthly temperature observations (i.e., spanning a century) for each grid cell at a 0.5-degree resolution. To construct country-level measures of the mean and standard deviation of temperature using this data set, the analysis at hand first computes the intertemporal moments of temperature across monthly observations at the grid-cell level and then averages these moments across grid cells that correspond to a given country.[8] As such, the volatility of temperature between 1901 and 2000 for a given country should be interpreted as the volatility prevalent in the "representative" grid cell within that country.

The qualitative interpretation of the empirical results is thus based on the identifying assumption that the cross-country distribution of temperature volatility during the 20th century was not significantly

[8] This sequence of computations was specifically chosen to minimize the information loss that inevitably results from aggregation. Note that an alternative (but not equivalent) sequence would have been to perform the spatial aggregation to the country level first and then compute the intertemporal moments. To see why this alternative is inferior, consider the extreme example of a country comprised of two grid cells that have identical temperature volatilities, but whose temperature fluctuations are perfectly negatively correlated. In this case, the alternative methodology would yield no volatility at all for the country as a whole, whereas the methodology adopted would yield the volatility prevalent in either of its grid cells.

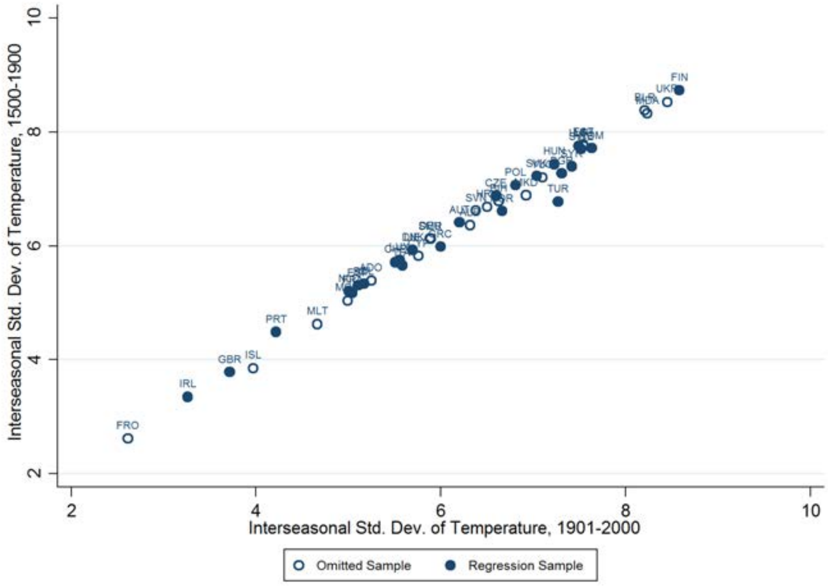


Figure 2: Contemporary vs. Historical Interseasonal Temperature Volatility

Notes: (i) Filled circles represent observations, comprising 25 countries in total, that appear in the samples exploited by the regression analyses in Tables 1–4, where sample sizes are constrained by the availability of data on covariates; (ii) The Pearson correlation between the interseasonal standard deviation of temperature in the 1901–2000 time period and that in the 1500–1900 time period is 0.993 in the restricted 25-country sample, and it is 0.995 in the unrestricted 45-country sample.

different from that which existed prior to the Neolithic Revolution. To relax this assumption somewhat, the analysis also employs a volatility measure constructed from new time-series data on historical temperature over the 1500–1900 time period (albeit for a smaller set of countries), revealing findings that are qualitatively similar to those uncovered using temperature volatility over the last century.

The historical time-series data on temperature are obtained from the recent data set of Luterbacher et al. (2006) who, in turn, compile their data from the earlier data sets of Luterbacher et al. (2004) and Xoplaki et al. (2005). These data sets make use of both directly measured data and, for earlier periods in the time series, proxy data from documentary evidence, tree rings, and ice cores to provide seasonal (from 1500 to 1658) and monthly (from 1659 onwards) temperature observations at a 0.5-degree resolution, primarily for the European continent. The current analysis then applies to these data an aggregation procedure, similar to that used for computing the measures of the intertemporal moments of contemporary temperature, in order to derive measures of the intertemporal mean and standard deviation of historical temperature at the country level. It should be noted that, while reliable historical and contemporary temperature data are commonly available for 45 countries (as depicted in the correlation plots in Figures 2 and 3), only 25 of these countries appear in the 97-country sample actually employed by the regressions to follow. This discrepancy is due to the unavailability of information on the timing of the agricultural transition and on some of the control variables employed by the regression analyses.[9]

[9] The distinction between the 45- and 25-country samples is evident in Figures 2 and 3, where observations appearing only in the 25-country sample are depicted as filled circles.

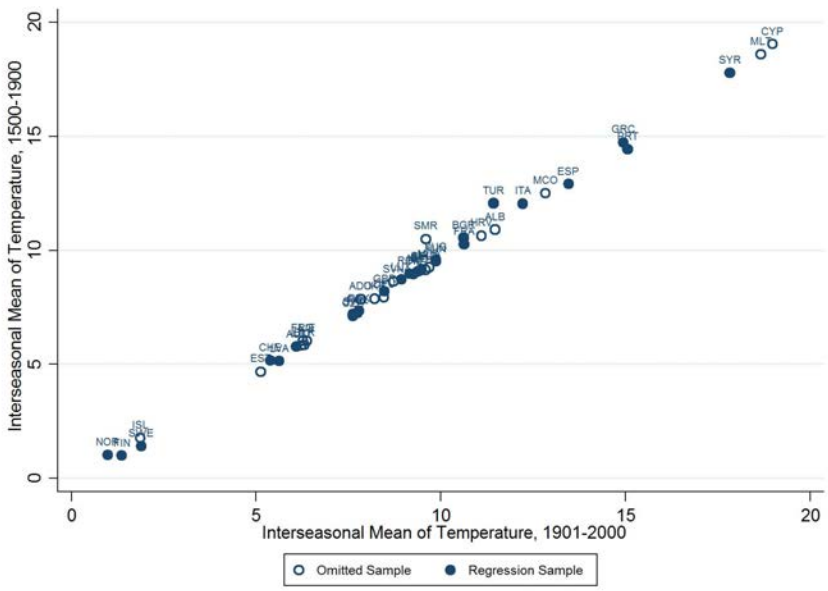


Figure 3: Contemporary vs. Historical Interseasonal Mean Temperature

Notes: (i) Filled circles represent observations, comprising 25 countries in total, that appear in the samples exploited by the regression analyses in Tables 1–4, where sample sizes are constrained by the availability of data on covariates; (ii) The Pearson correlation between the interseasonal mean of temperature in the 1901–2000 time period and that in the 1500–1900 time period is 0.998 in both the restricted 25-country sample and the unrestricted 45-country sample.

Consistent with the assertion that the spatial variation in temperature volatility remains largely stable over long periods of time, temperature volatility during the 20th century and that during the preceding four centuries are highly positively correlated across countries, possessing a correlation coefficient of 0.995 in the 45-country sample. This relationship is depicted on the scatter plot in Figure 2, where it is important to note that the rank order of the vast majority of countries is maintained across the two time horizons. Moreover, as depicted in Figure 3, a similarly strong correlation exists between the mean of temperature during the 20th century and that during the preceding four centuries, lending further credence to the identifying assumption that contemporary data on climatic factors can be meaningfully employed as informative proxies for prehistoric ones.

The country-level data on the timing of the Neolithic Revolution are obtained from the data set of Putterman (2008), who assembles this variable using a wide variety of both regional and country-specific archaeological studies, as well as more general encyclopedic works on the Neolithic transition, including MacNeish (1992) and Smith (1995).[10] Specifically, the reported measure captures the number of thousand years elapsed, relative to the year 2000, since the earliest recorded date when a region within a country's present borders underwent the transition from primary reliance on hunted and gathered food sources to primary reliance on cultivated crops (and livestock).

Formally, in light of the theoretical prediction regarding the non-monotonic relationship between climatic volatility and the timing of the transition to agriculture, the following quadratic specification is

[10]For a detailed description of the primary and secondary data sources employed by the author in the construction of this variable, the reader is referred to the website of the *Agricultural Transition Data Set*.

estimated:

$$YST_i = \beta_0 + \beta_1 VOL_i + \beta_2 VOL_i^2 + \beta_3 TMEAN_i + \beta_4 LDIST_i + \beta_5 LAT_i + \beta_6 AREA_i + \boldsymbol{\beta}_7^{'}\boldsymbol{\Delta}_i + \boldsymbol{\beta}_8^{'}\boldsymbol{\Gamma}_i + \varepsilon_i,$$

where YST_i is the number of thousand years elapsed since the Neolithic Revolution in country i, as reported by Putterman (2008); VOL_i is the temperature volatility prevalent in country i during either the contemporary (1901–2000) or the historical (1500–1900) time horizon; $TMEAN_i$ is the mean temperature (in degrees Celsius) of country i during the corresponding time period; $LDIST_i$ is the log of the great-circle distance (in kilometers) to the closest Neolithic frontier, included here as a control for the timing of the arrival of agricultural practices via spatial technological diffusion from the frontier;[11] LAT_i is the absolute latitude (in degrees) of the geodesic centroid of country i, and $AREA_i$ is the total land area (in millions of square kilometers) of country i, as reported by the 2008 *CIA World Factbook*;[12] $\boldsymbol{\Delta}_i$ is a vector of continental dummies; $\boldsymbol{\Gamma}_i$ is a vector of biogeographic variables employed by the study of Olsson and Hibbs (2005), such as climate, the size and geographic orientation of the landmass, and the numbers of prehistoric domesticable species of plants and animals, included here as controls for the impact of biogeographic endowments as hypothesized by Diamond (1997); and, finally, ε_i is a country-specific disturbance term.

To fix priors, the reduced-form prediction of the theory – i.e., that intermediate levels of climatic volatility should be associated with an earlier adoption of agriculture – implies that, in the context of the regression specification, the timing of the Neolithic Revolution, YST_i, and temperature volatility, VOL_i, should be characterized by a hump-shaped relationship across countries – i.e., $\beta_1 > 0$, $\beta_2 < 0$, and $VOL^* = -\beta_1/(2\beta_2) \in \left(VOL^{\min}, VOL^{\max}\right)$.[13]

Before proceeding to the empirical findings, one issue that merits further discussion is the use of countries as the unit of analysis. While arguments could be made regarding the extent to which regions delineated by modern national borders are related to economically meaningful regions from thousands of years ago, there are at least two reasons for following this particular course. First, comparable data with uniform *global* coverage on the timing of the Neolithic Revolution are currently only available at the country level. Second, given that previous literature has linked the timing of the Neolithic Revolution to both contemporary and historical comparative development across countries, one would naturally like to explore the forces behind the emergence of agriculture at this level of aggregation. Regardless of these considerations, however, as will become evident, the uncovered relationship between temperature volatility and the timing of the agricultural transition does not appear to be a statistical artifact of the chosen unit of analysis, since a qualitatively similar finding is obtained when exploiting observed heterogeneity either across countries or across archaeological sites.

[11] Distances to the closest Neolithic frontier are computed with the haversine formula, using the coordinates of modern country capitals as spatial endpoints. The set of seven global Neolithic frontiers, considered in the determination of the closest frontier for each observation, comprises Syria, China, Ethiopia, Niger, Mexico, Peru, and Papua New Guinea. To maximize the degrees of freedom exploited by the regressions – i.e., permitting them to incorporate all the available information, including that on the frontiers themselves – the log transformation is applied to one plus the underlying distance variable.

[12] The inclusion of land area as a control variable is meant to capture the potentially confounding effects of population and geographic scale on innovative activity (Kremer, 1993). Specifically, in a world where (i) population size is increasing in land area and (ii) the incidence of an innovation amongst the population in any given location follows a point-Poisson process, larger land areas are expected to be associated with more innovations – i.e., an *a priori* earlier transition to agriculture in the context of the current study.

[13] These conditions ensure not only strict concavity, but also that the optimal volatility implied by the first- and second-order coefficients falls within the domain of temperature volatility observed in the cross-country sample.

4.1.1 Results with Contemporary Volatility

Table 1 reveals the results from regressions employing temperature volatility computed from contemporary time-series data. Specifically, the measure of volatility used is the intertemporal standard deviation of monthly temperature (in degrees Celsius) across 1,200 observations spanning the 1901–2000 time horizon. For the sample of 97 countries employed by this exercise, the volatility measure assumes a minimum value of 0.548 (for Rwanda), a maximum value of 10.082 (for China), and a sample mean and standard deviation of 3.995 and 2.700, respectively.[14]

Column 1 of Table 1 reveals a highly statistically significant hump-shaped relationship between the timing of the Neolithic Revolution and temperature volatility, conditional on mean temperature, log-distance to the closest Neolithic frontier, absolute latitude, land area, and continent fixed effects. In particular, the first- and second-order coefficients on temperature volatility are both statistically significant at the 1% level and possess their expected signs. The coefficients of interest imply that the optimal level of temperature volatility for the Neolithic transition to agriculture is 8.203, an estimate that is also statistically significant at the 1% level. To interpret the overall metric effect implied by these coefficients, a one-degree-Celsius change in temperature volatility on either side of the optimum is associated with a delay in the onset of the Neolithic Revolution by 79 years.[15]

As for the control variables in the specification from Column 1, the significant negative coefficient on log-distance to the Neolithic frontier is consistent with priors regarding the spatial diffusion of agricultural practices from the frontier, whereas the positive (albeit statistically insignificant) coefficient on land area is in line with Kremer's (1993) findings regarding the presence of scale effects throughout human history. Moreover, the coefficient on absolute latitude indicates that latitudinal bands closer to the equator are associated with an earlier transition to agriculture.

The remainder of the analysis in Table 1 is concerned with ensuring that the relationship between volatility and the timing of the Neolithic is not an artefact of the correlation between climatic volatility and other geographic and biogeographic endowments that have been deemed important for the adoption of agriculture by the previous literature. Thus, the specification examined in Column 2 augments the preceding analysis with controls for geographic variables from the study of Olsson and Hibbs (2005), including an index gauging climatic favorability for agriculture, as well as the size and orientation of the landmass, which, as argued by Diamond (1997), played an important role by enhancing the availability of domesticable species and by facilitating the diffusion of agricultural technologies along similar environments. Column 3 repeats this analysis using the first principal component of the aforementioned geographic controls, a variable used by Olsson and Hibbs (2005) to test Diamond's (1997) hypothesis.

The baseline specification from Column 1 is augmented with controls for the numbers of prehistoric domesticable species of plants and animals in Column 4, while Column 5 replicates this same exercise using the first principal component of these biogeographic variables. The next two columns demonstrate robustness to the combined set of geographic and biogeographic controls from Olsson and Hibbs's (2005) empirical

[14] These descriptive statistics, along with those of the control variables employed by the analysis, are collected in Table B.1 in Appendix B, with the relevant correlations appearing in Table B.2.

[15] Note that this is different from the marginal effect, which by definition would be zero at the optimum. The difference between the marginal and metric effects arises from the fact that a one-degree-Celsius change in temperature volatility does not constitute an infinitesimal change in this variable, as required by the calculation of its marginal effect. It is easy to show that the metric effect of a ΔVOL change in volatility at the level $\overline{VOL}$ is given by $\Delta YST = \beta_1 \Delta VOL + \beta_2 \left(2\overline{VOL} + \Delta VOL\right) \Delta VOL$. Evaluating this expression at the optimum for a one-degree-Celsius change in volatility – i.e., setting $\Delta VOL = 1$ and $\overline{VOL} = -\beta_1 / (2\beta_2)$ – yields the relevant metric effect reported in the text.

Table 1: The Timing of the Neolithic Revolution and Contemporary Intermonthly Temperature Volatility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent Variable is Thousand Years Elapsed since the Neolithic Revolution								
Temperature Volatility	1.292***	0.814***	0.998***	1.183***	1.053***	0.924***	0.940***	1.187***	1.180***
	(0.298)	(0.239)	(0.288)	(0.246)	(0.233)	(0.217)	(0.237)	(0.358)	(0.386)
Temperature Volatility Square	-0.079***	-0.050**	-0.070***	-0.085***	-0.075***	-0.064***	-0.071***	-0.083***	-0.088***
	(0.028)	(0.022)	(0.026)	(0.022)	(0.021)	(0.019)	(0.021)	(0.030)	(0.033)
Mean Temperature	0.022	0.074**	0.034	-0.018	-0.003	0.030	0.004	0.037	0.014
	(0.041)	(0.028)	(0.037)	(0.036)	(0.035)	(0.028)	(0.033)	(0.069)	(0.072)
Log Distance to Frontier	-0.260***	-0.273***	-0.262***	-0.208***	-0.235***	-0.209***	-0.239***	-0.220***	-0.247***
	(0.091)	(0.049)	(0.075)	(0.063)	(0.065)	(0.047)	(0.060)	(0.052)	(0.067)
Absolute Latitude	-0.097***	-0.073***	-0.066**	-0.129***	-0.117***	-0.104***	-0.101***	-0.110***	-0.109***
	(0.024)	(0.023)	(0.029)	(0.018)	(0.018)	(0.019)	(0.020)	(0.033)	(0.031)
Land Area	0.021	0.101	0.081	0.193*	0.148*	0.204*	0.163**	0.192	0.132
	(0.065)	(0.069)	(0.058)	(0.100)	(0.085)	(0.107)	(0.081)	(0.124)	(0.087)
Climate		0.991***				0.577***		0.530**	
		(0.196)				(0.208)		(0.234)	
Orientation of Landmass		-0.682***				-1.103***		-1.083***	
		(0.231)				(0.284)		(0.339)	
Size of Landmass		0.042***				0.049***		0.048***	
		(0.012)				(0.011)		(0.012)	
Geographic Conditions			0.593***				0.273**		0.299
			(0.184)				(0.130)		(0.181)
Domesticable Plants				0.121***		0.116***		0.118***	
				(0.027)		(0.024)		(0.027)	
Domesticable Animals				-0.005		-0.182		-0.186	
				(0.121)		(0.110)		(0.119)	
Biogeographic Conditions					1.287***		1.165***		1.121***
					(0.265)		(0.260)		(0.286)
Mean Elevation								0.030	0.043
								(0.049)	(0.051)
Mean Ruggedness								-0.050	-0.133
								(0.115)	(0.126)
% Land in Tropical Zones								0.679	0.554
								(0.419)	(0.546)
% Land in Temperate Zones								0.702	0.789
								(0.437)	(0.494)
Landlocked Dummy	No	No	No	No	No	No	No	Yes	Yes
Small Island Dummy	No	No	No	No	No	No	No	Yes	Yes
Continent Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Optimal Temperature Volatility	8.203***	8.141***	7.124***	6.960***	7.062***	7.260***	6.627***	7.167***	6.673***
	(1.378)	(1.859)	(1.272)	(0.610)	(0.780)	(0.842)	(0.805)	(0.848)	(0.793)
F-test p-value	$<$0.001	0.002	0.003	$<$0.001	$<$0.001	$<$0.001	$<$0.001	0.003	0.009
Observations	97	97	97	97	97	97	97	97	97
Adjusted R^2	0.73	0.83	0.76	0.84	0.83	0.88	0.84	0.88	0.84

Notes: (i) Temperature volatility is the intermonthly standard deviation of monthly temperature across 1,200 observations spanning the 1901–2000 time period, and mean temperature is the intermonthly average across these observations; (ii) Geographic conditions is the first principal component of climate, and the size and orientation of the landmass; (iii) Biogeographic conditions is the first principal component of domesticable plants and animals; (iv) The excluded continental category in all regressions is Oceania; (v) A single continental category is used to represent the Americas, which is appropriate for the prehistoric outcome variable being examined; (vi) The F-test p-value is from the joint-significance test of the linear and quadratic terms of temperature volatility; (vii) Heteroskedasticity robust standard error estimates are reported in parentheses; (viii) The standard error estimate for the optimal temperature volatility is computed via the delta method; (ix) *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

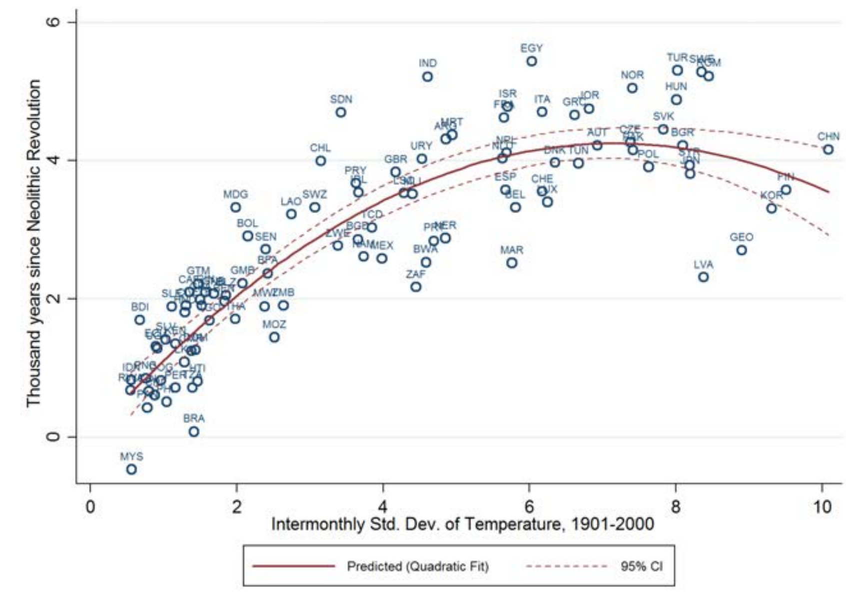


Figure 4: Contemporary Intermonthly Temperature Volatility vs. the Timing of the Neolithic Revolution

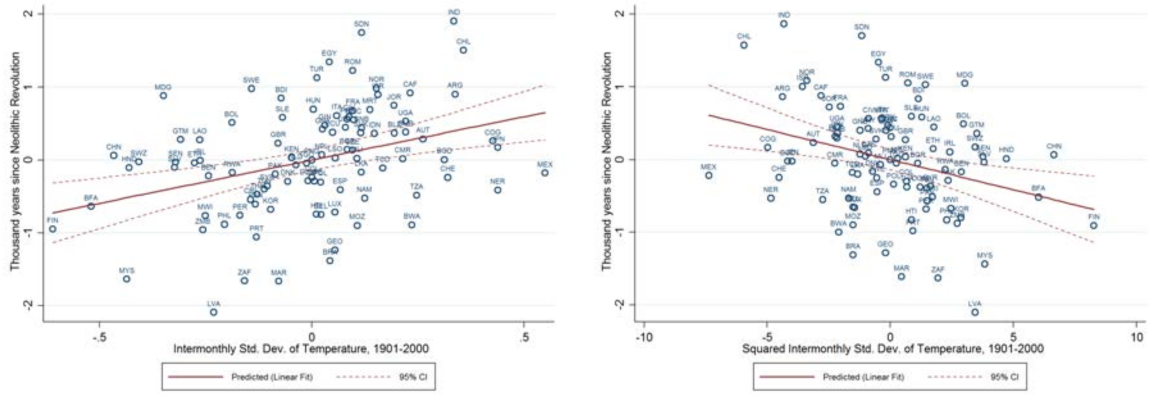
Notes: (i) The depicted relationship reflects a quadratic fit of the relevant data on an "augmented component plus residual" plot (see the discussion in footnote 17 for additional details); (ii) The underlying regression corresponds to the specification examined in Column 8 of Table 1.

exercise, with the relevant controls entering the regression specification either as individual covariates in Column 6 or as principal components in Column 7. Finally, Columns 8 and 9 further augment the specifications from the previous two columns with controls for elevation, a measure capturing the degree of terrain undulation, the percentages of land in tropical and temperate climatic zones, and small island and landlocked dummies, capturing additional fixed effects potentially important for the diffusion and implementation of agricultural technologies.[16]

The overall hump-shaped effect of temperature volatility on the timing of the Neolithic transition, conditional on the full set of controls in Column 8, is depicted on the scatter plot in Figure 4, while the associated first- and second-order partial effects of volatility – i.e., the regression lines corresponding to its first- and second-order coefficients – are depicted in Figures 5(a)–5(b).[17] As illustrated in Figure 4, the coefficients of interest from Column 8 imply that a one-degree-Celsius change in temperature volatility on either side of the optimum is associated with an 83-year delay in the onset of agriculture.

[16] In terms of the data sources for the additional controls, the data on mean elevation and terrain undulation (ruggedness) by country are derived from the *G-Econ* project of Nordhaus (2006), while data on the percentages of land area in tropical and temperate climatic zones are taken from the data set of Gallup, Sachs and Mellinger (1999). Finally, the island and landlocked dummies are constructed based on data from the 2008 *CIA World Factbook*.

[17] It should also be noted that Figures 4, 6, 7, and 9 are "augmented component plus residual" plots and not the typical "added variable" plots of residuals against residuals. In particular, the vertical axes in these figures represent the component of transition timing that is explained by temperature volatility and its square, plus the residuals from the corresponding regression. The horizontal axes, on the other hand, simply represent temperature volatility rather than the residuals obtained from regressing volatility on the covariates. This methodology permits the illustration of the overall non-monotonic effect of temperature volatility in one scatter plot per regression, with the regression line being generated by a quadratic fit of the y-axis variable (explained above) on the x-axis variable (temperature volatility).



(a) The First-Order Effect

(b) The Second-Order Effect

Figure 5: The First- and Second-Order Effects of Contemporary Intermonthly Temperature Volatility

Notes: (i) Each depicted relationship reflects a linear fit of the relevant data on an "added variable" (partial regression) plot; (ii) The underlying regression corresponds to the specification examined in Column 8 of Table 1.

As is evident from Table 1, the hump-shaped effect of temperature volatility on the timing of the Neolithic Revolution, revealed in Column 1, remains both quantitatively and qualitatively robust when subjected to a variety of controls for geographic and biogeographic endowments. With regard to the control variables, absolute latitude and log-distance to the Neolithic frontier appear to consistently confer effects across specifications that are in line with priors, whereas the effects associated with the geographic and biogeographic variables, as examined by Olsson and Hibbs (2005), are largely consistent with the results of their empirical exercise.

To summarize, the findings uncovered in Table 1, while validating the importance of technology diffusion and geographic and biogeographic endowments, provide reassurance that the significant hump-shaped effect of temperature volatility on the timing of the Neolithic Revolution is not simply a spurious relationship, attributable to other channels highlighted in the previous literature, but one that plausibly reflects the novel empirical predictions of the proposed theory.

Accounting for Seasonality One obvious shortcoming of the measure of temperature volatility employed by the analysis thus far is that, since it is derived as the *intermonthly* standard deviation of temperature in the 1901–2000 time frame, it captures a systematic component of temperature volatility that is purely due to seasonality. Given that seasonality may potentially be correlated with unobserved (or observed but noisily measured) geographic determinants of the timing of the Neolithic Revolution, if seasonality alone is driving the observed hump-shaped pattern, then the interpretation of the results as being supportive of the proposed theory becomes somewhat suspect. Indeed, while the inclusion of absolute latitude as a control variable in the specifications partially mitigates the seasonality issue, it is far from perfect.

To rigorously address this issue, the analysis at hand employs measures of season-specific interannual temperature volatility over the 1901-2000 time horizon. In constructing these volatility measures, the monthly temperature observations from the CRU TS 2.0 data set are first aggregated into seasonal ones while accounting for North-South hemisphericity – i.e., for countries in the Northern/Southern Hemisphere,

Table 2: The Timing of the Neolithic Revolution and Contemporary Interannual Season-Specific Temperature Volatility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is Thousand Years Elapsed since the Neolithic Revolution							
	Interannual Volatility and Mean of Seasonal Temperature (1901–2000) using Observations on:							
	Spring Seasons		Summer Seasons		Autumn Seasons		Winter Seasons	
Temperature Volatility	9.766***	6.054***	10.591**	9.984**	12.180***	7.374**	6.295***	4.905***
	(2.646)	(2.211)	(4.634)	(4.733)	(3.578)	(3.688)	(1.200)	(1.538)
Temperature Volatility Square	-4.844***	-3.440***	-6.869*	-8.226**	-5.586***	-3.864*	-2.031***	-1.566***
	(1.335)	(1.138)	(3.630)	(3.499)	(1.995)	(1.987)	(0.367)	(0.438)
Mean Temperature	-0.013	0.066	0.094**	0.080	0.052	0.098	-0.001	0.079
	(0.038)	(0.048)	(0.045)	(0.052)	(0.042)	(0.064)	(0.035)	(0.053)
Log Distance to Frontier	-0.273***	-0.212***	-0.278***	-0.200***	-0.265***	-0.215***	-0.252***	-0.191***
	(0.090)	(0.053)	(0.081)	(0.048)	(0.081)	(0.054)	(0.078)	(0.051)
Absolute Latitude	-0.030	-0.049**	-0.007	-0.041*	-0.046*	-0.047*	-0.035	-0.041
	(0.025)	(0.024)	(0.021)	(0.022)	(0.024)	(0.025)	(0.022)	(0.025)
Land Area	0.054	0.135*	0.047	0.102	0.033	0.130	0.028	0.111
	(0.075)	(0.079)	(0.067)	(0.070)	(0.069)	(0.090)	(0.081)	(0.090)
Geographic Conditions		0.515***		0.582***		0.482***		0.514***
		(0.155)		(0.166)		(0.172)		(0.160)
Biogeographic Conditions		1.145***		1.066***		1.034***		1.025***
		(0.293)		(0.285)		(0.285)		(0.291)
Mean Elevation		0.075*		0.071		0.080*		0.105**
		(0.042)		(0.043)		(0.048)		(0.050)
Mean Ruggedness		-0.213		-0.226*		-0.155		-0.255*
		(0.131)		(0.128)		(0.126)		(0.138)
% Land in Tropical Zones		-0.218		-0.133		0.159		-0.107
		(0.468)		(0.619)		(0.629)		(0.450)
% Land in Temperate Zones		0.966*		0.535		0.767		0.803
		(0.540)		(0.475)		(0.536)		(0.537)
Landlocked Dummy	No	Yes	No	Yes	No	Yes	No	Yes
Small Island Dummy	No	Yes	No	Yes	No	Yes	No	Yes
Continent Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Optimal Temperature Volatility	1.008***	0.880***	0.771***	0.607***	1.090***	0.954***	1.550***	1.566***
	(0.086)	(0.105)	(0.133)	(0.063)	(0.126)	(0.154)	(0.094)	(0.172)
F-test p-value	0.002	0.012	0.052	0.046	0.002	0.141	<0.001	0.002
Observations	97	97	97	97	97	97	97	97
Adjusted R^2	0.69	0.84	0.69	0.83	0.71	0.83	0.71	0.84

Notes: (i) Temperature volatility is the interannual standard deviation of seasonal temperature across 100 season-specific observations spanning the 1901–2000 time period, and mean temperature is the interannual average across these observations; (ii) Monthly temperature observations are first aggregated into seasonal ones while accounting for North-South hemisphericity, that is, in the Northern/Southern Hemisphere, the seasons are defined as follows: Spring/Autumn (Mar-Apr-May), Summer/Winter (Jun-Jul-Aug), Autumn/Spring (Sep-Oct-Nov), Winter/Summer (Dec-Jan-Feb); (iii) Geographic conditions is the first principal component of climate, and the size and orientation of the landmass; (iv) Biogeographic conditions is the first principal component of domesticable plants and animals; (v) The excluded continental category in all regressions is Oceania; (vi) A single continental category is used to represent the Americas, which is appropriate for the prehistoric outcome variable being examined; (vii) The F-test p-value is from the joint significance test of the linear and quadratic terms of temperature volatility; (viii) Heteroskedasticity robust standard error estimates are reported in parentheses; (ix) The standard error estimate for the optimal temperature volatility is computed via the delta method; (x) *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

the mapping of months into seasons is defined as follows: March-April-May (Spring/Autumn), June-July-August (Summer/Winter), September-October-November (Autumn/Spring), December-January-February (Winter/Summer). For any given season, the relevant temperature-volatility measure is then calculated as the interannual standard deviation of seasonal temperature (in degrees Celsius) across the 100 season-specific observations spanning the 1901–2000 time period.[18]

Table 2 presents the results from regressions examining, one at a time, each of the four season-specific temperature-volatility measures as a non-monotonic determinant of the timing of the Neolithic Revolution. In particular, for each season-specific volatility measure, two specifications are considered, one with the baseline set of controls (corresponding to Column 1 of Table 1), and the other with the full set of controls (corresponding to Column 9 of Table 1). As is evident from the table, for each season examined, the regressions reveal a statistically significant and qualitatively robust hump-shaped effect of volatility on the timing of the Neolithic Revolution. Specifically, the estimated first- and second-order coefficients on volatility not only appear with their expected signs, but they also maintain statistical significance and remain largely stable in magnitude when subjected to the full set of controls for geographic and biogeographic endowments. The same general pattern is reflected by the corresponding estimates of optimal volatility implied by these first- and second-order coefficients.

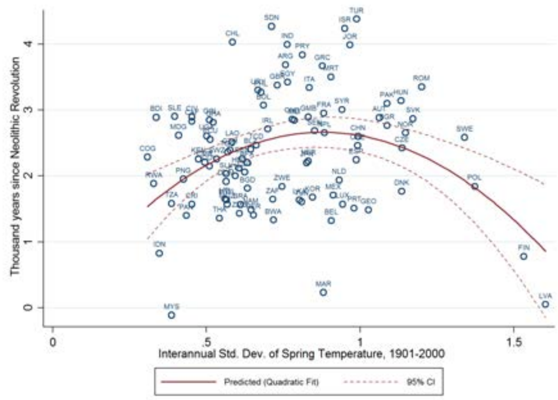
The scatter plots in Figures 6(a)–6(d) depict the overall hump-shaped effects of the four season-specific temperature-volatility measures on the timing of the Neolithic transition, conditional on the full set of controls.[19] To interpret the overall metric effect associated with each season-specific set of coefficient estimates, a one-degree-Celsius change on either side of the optimum in spring, summer, autumn, and winter temperature volatility delays the adoption of Neolithic agriculture by 3,440, 8,226, 3,864, and 1,566 years, respectively.

The following thought experiment places the aforementioned effects of season-specific volatility into perspective. If the Republic of Congo's low spring temperature volatility of 0.308 were increased to Greece's spring volatility of 0.877, which is in the neighborhood of the optimum, then, all else equal, agriculture would have appeared in the Republic of Congo by 4,125 Before Present (BP) instead of 3,000 BP, reducing the gap in the timing of the transition between the two countries by allowing the Republic of Congo to reap the benefits of agriculture 1,125 years earlier. At the other end of the spectrum, lowering Latvia's high spring temperature volatility of 1.604 to that of Greece would have accelerated the adoption of farming in the regions belonging to Latvia today by 1,802 years.

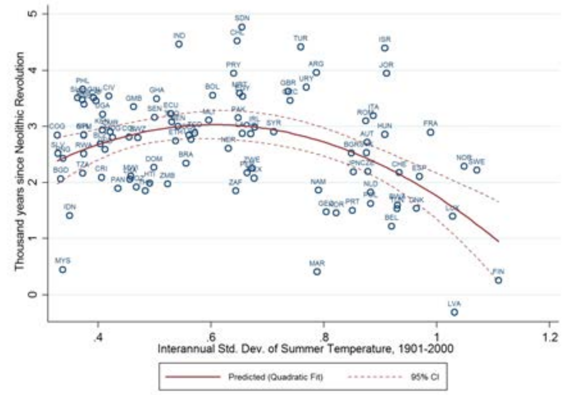
Comparing the magnitudes of the coefficients of interest across seasons in Table 2, the regressions indicate a lower relative importance of interannual winter temperature volatility. This pattern is corroborated by Table 3, which collects the results from Wald tests conducted to examine whether the first- and second-order effects of winter volatility, as presented in Table 2, are significantly different from the corresponding effects of the volatility measures for the other seasons. The relatively weaker impact of winter volatility, revealed in Table 2, is entirely consistent with the prior that knowledge accumulation in the hunter-gatherer regime was more likely to have been useful for agriculture when the possibility of farming was present, which

[18] The relevant descriptive statistics of the four season-specific volatility measures and their correlations with the control variables employed by the regressions to follow are reported in Appendix B, in Tables B.3 and B.4, respectively.

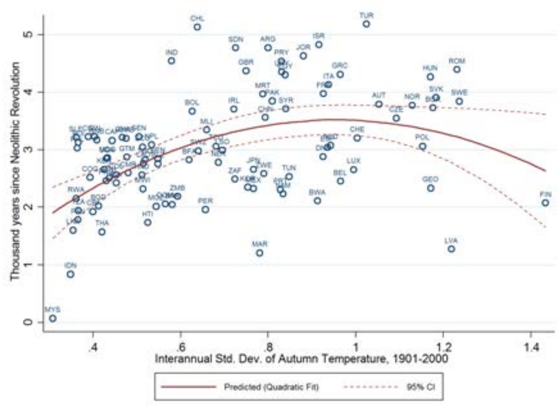
[19] The associated first- and second-order partial effects of the season-specific temperature-volatility measures – i.e., the regression lines corresponding to their first- and second-order coefficients – are depicted in panels (a) and (b), respectively, of Figures A.1–A.4 in Appendix A.



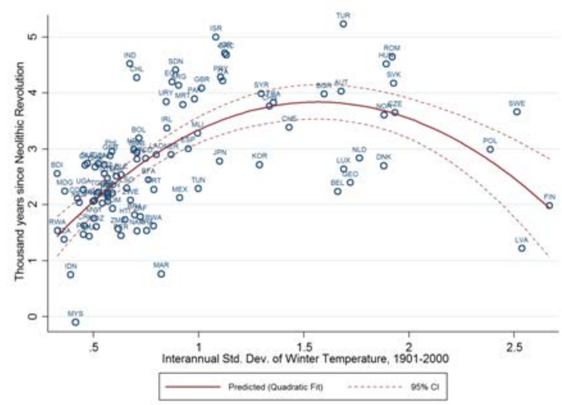
(a) Spring Volatility



(b) Summer Volatility



(c) Autumn Volatility



(d) Winter Volatility

Figure 6: Contemporary Interannual Season-Specific Temperature Volatility vs. the Timing of the Neolithic Revolution

Notes: (i) Each depicted relationship reflects a quadratic fit of the relevant data on an "augmented component plus residual" plot (see the discussion in footnote 17 for additional details); (ii) The underlying regressions correspond to the specifications examined in even-numbered columns of Table 2.

is less so during winter seasons.[20] This finding is also in line with the argument that the greater constraint on resource availability during winter seasons would have been rationally anticipated by hunter-gatherers and thus accounted for in their food procurement activities. As such, winter temperature volatility should be expected to have played a relatively smaller role in shaping the subsistence strategies and the associated knowledge accumulation of hunter-gatherers towards the adoption of agriculture.

In sum, the results uncovered in Table 2, while being quantitatively different from those associated with the baseline measure of temperature volatility in Table 1, establish the qualitative robustness of the

[20] An alternative way to gauge the relative importance of the season-specific volatilities would have been to simultaneously include all four season-specific measures in the same regression specification. Nevertheless, given the high sample correlations between these respective measures, as evident in Table B.4 in Appendix B, the resulting regression would be rather uninformative due to the well-known consequences of multicollinearity.

Table 3: Wald Tests for Assesing the Relative Importance of Winter Volatility

	(1)	(2)	(3)	(4)	(5)	(6)
	$\chi^2(1)$ Statistic from Wald Tests of the Null Hypotheses that the Effects of Winter Volatility are not Different from the Effects of:					
	Spring Volatility		Summer Volatility		Autumn Volatility	
	Baseline Model	Full Model	Baseline Model	Full Model	Baseline Model	Full Model
Test on the First-Order Effect	2.49	0.44	1.07	1.85	3.84**	0.77
	[0.115]	[0.508]	[0.300]	[0.174]	[0.050]	[0.379]
Test on the Second-Order Effect	6.43**	5.03**	2.09	5.08**	4.21**	2.03
	[0.011]	[0.025]	[0.149]	[0.024]	[0.040]	[0.154]

Notes: (i) Odd-numbered columns in this table compare the relevant coefficient estimates from the specification presented in Column 7 of Table 2 with corresponding ones presented in Columns 1, 3, and 5, respectively, of that table; (ii) Even-numbered columns in this table compare the relevant coefficient estimates from the specification presented in Column 8 of Table 2 with corresponding ones presented in Columns 2, 4, and 6, respectively, of that table;(i) *p*-values of the $\chi^2(1)$ statistics are reported in square brackets; (ii) *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

baseline findings to the issue of seasonality.[21] This lends support to the assertion that the significant and robust hump-shaped effect of temperature volatility on the timing of the Neolithic Revolution is not being driven by systematic intertemporal fluctuations due to seasonality, a finding that would otherwise have been at odds with the predictions of the proposed theory.

4.1.2 Results with Historical Volatility

As discussed earlier, the interpretation of the results for measures of contemporary temperature volatility rests on the identifying assumption that the cross-country distribution of temperature volatility during the 20th century was not significantly different from that which existed prior to the Neolithic Revolution. In an effort to relax this assumption, this section focuses on establishing qualitatively similar findings using a measure of volatility computed from historical time-series temperature data.

In particular, given that the historical time series is partially composed of seasonal (rather than monthly) temperature observations, the measure of volatility employed by this exercise is the intertemporal standard deviation of seasonal temperature (in degrees Celsius) across 1,604 observations spanning the 1500–1900 time period. As mentioned previously, the cross-country sample considered here comprises 25 primarily European observations, selected based on the condition that data on the standard set of control variables are available for these countries and that they also appear in the 97-country sample considered earlier. This permits fair comparisons of the effects of the volatility measures for the contemporary versus historical time frames in the same sample of countries.[22] In this modest 25-country sample, the measure of

[21] The finding that the metric effects of the season-specific temperature-volatility measures are larger than those uncovered in Table 1 may reflect the fact that non-seasonality-adjusted volatility additionally captures *expected* movements in temperature over time, which, by virtue of having been rationally anticipated, were less likely to instigate novel changes in hunter-gatherer subsistence strategies.

[22] While historical time-series temperature data are available for some countries in North Africa and the Near East as well, the data are considered to be far more reliable for European countries, where the number of weather stations is substantially larger and more uniformly distributed across space. In addition, there is no evidence of systematic climatic reversals amongst European countries since the Last Glacial Maximum, unlike, for example, in North Africa where expansions of the Sahara has resulted in increased desertification over time.

Table 4: The Timing of the Neolithic Revolution and Historical vs. Contemporary Interseasonal Temperature Volatility

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable is Thousand Years Elapsed since the Neolithic Revolution							
	Interseasonal Volatility and Mean of Seasonal Temperature for the:							
	Historical Period (1500–1900)				Contemporary Period (1901–2000)			
Temperature Volatility	5.367***	4.642***	4.521***	3.712***	5.063***	4.224***	4.123***	3.185***
	(0.767)	(0.710)	(1.068)	(0.875)	(0.680)	(0.618)	(1.093)	(0.968)
Temperature Volatility Square	-0.402***	-0.343***	-0.354***	-0.287***	-0.389***	-0.318***	-0.335***	-0.256***
	(0.061)	(0.053)	(0.077)	(0.060)	(0.055)	(0.045)	(0.079)	(0.064)
Mean Temperature	0.173**	0.145**	-0.047	-0.088	0.164**	0.127	-0.124	-0.191
	(0.061)	(0.067)	(0.377)	(0.314)	(0.062)	(0.073)	(0.344)	(0.296)
Log Distance to Frontier	-0.054	-0.100	-0.176	-0.239*	-0.002	-0.079	-0.157	-0.256
	(0.125)	(0.120)	(0.128)	(0.129)	(0.124)	(0.121)	(0.137)	(0.152)
Absolute Latitude	-0.096**	-0.096**	-0.203	-0.204	-0.106**	-0.107**	-0.248	-0.259
	(0.035)	(0.035)	(0.183)	(0.155)	(0.037)	(0.039)	(0.169)	(0.147)
Land Area	1.589	1.900*	2.972***	3.301***	1.360	1.827*	2.789***	3.282**
	(1.170)	(1.005)	(0.853)	(1.062)	(1.176)	(1.020)	(0.872)	(1.205)
Climate	-0.940		-0.981		-1.070*		-1.045	
	(0.541)		(0.627)		(0.573)		(0.683)	
Orientation of Landmass	2.498***		2.547**		2.168**		2.183**	
	(0.808)		(0.968)		(0.763)		(0.926)	
Size of Landmass	-0.163***		-0.148**		-0.144***		-0.126**	
	(0.037)		(0.052)		(0.034)		(0.050)	
Geographic Conditions		-0.787***		-0.541**		-0.700***		-0.424*
		(0.213)		(0.237)		(0.191)		(0.237)
Mean Elevation			-0.318	-0.349			-0.344	-0.394
			(0.281)	(0.243)			(0.263)	(0.244)
Mean Ruggedness			0.302	0.403			0.275	0.390
			(0.257)	(0.234)			(0.245)	(0.233)
Landlocked Dummy	No	No	Yes	Yes	No	No	Yes	Yes
Europe Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Optimal Temperature Volatility	6.680***	6.772***	6.392***	6.478***	6.506***	6.645***	6.157***	6.221***
	(0.236)	(0.214)	(0.398)	(0.386)	(0.242)	(0.222)	(0.418)	(0.475)
F-test p-value	<0.001	<0.001	0.002	<0.001	<0.001	<0.001	0.004	<0.001
Observations	25	25	25	25	25	25	25	25
Adjusted R^2	0.90	0.89	0.90	0.89	0.89	0.89	0.90	0.89

Notes: (i) For the 1500–1900 time period, temperature volatility is the interseasonal standard deviation of seasonal temperature across 1,604 observations spanning this period, and mean temperature is the interseasonal average across these observations; (ii) For the 1901–2000 time period, temperature volatility is the interseasonal standard deviation of seasonal temperature across 400 observations spanning this period, and mean temperature is the interseasonal average across these observations; (iii) For the 1901–2000 time period, monthly temperature observations are first aggregated into seasonal ones, and since all countries in the sample appear in the Northern Hemisphere, the seasons are defined as follows: Spring (Mar-Apr-May), Summer (Jun-Jul-Aug), Autumn (Sep-Oct-Nov), Winter (Dec-Jan-Feb); (iv) Geographic conditions is the first principal component of climate, and the size and orientation of the landmass; (v) Biogeographic conditions is the first principal component of domesticable plants and animals; (vi) The excluded continental category in all regressions is Asia; (vii) The F-test p-value is from the joint significance test of the linear and quadratic terms of temperature volatility; (viii) Heteroskedasticity robust standard error estimates are reported in parentheses; (ix) The standard error estimate for the optimal temperature volatility is computed via the delta method; (x) *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

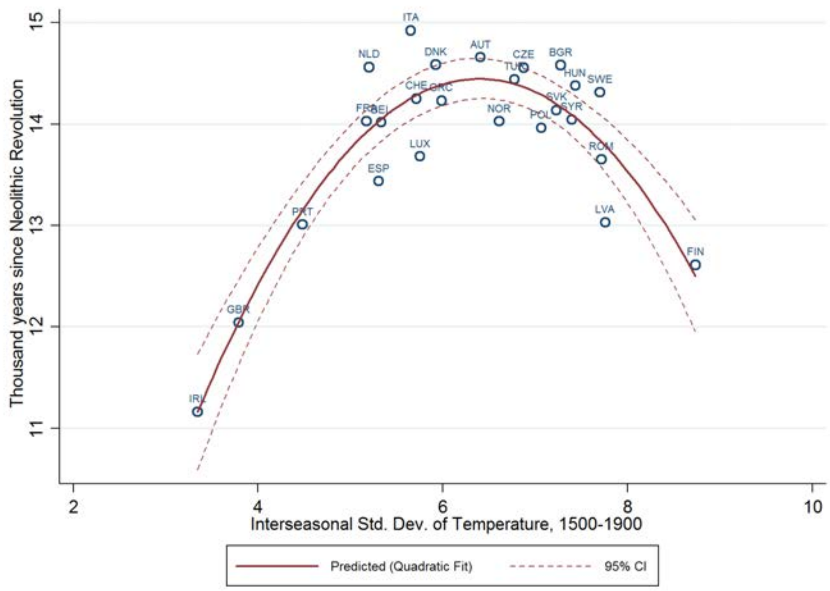


Figure 7: Historical Interseasonal Temperature Volatility vs. the Timing of the Neolithic Revolution

Notes: (i) The depicted relationship reflects a quadratic fit of the relevant data on an "augmented component plus residual" plot (see the discussion in footnote 17 for additional details); (ii) The underlying regression corresponds to the specification examined in Column 3 of Table 4.

historical temperature volatility assumes a minimum value of 3.345 (for Ireland), a maximum value of 8.736 (for Finland), and a sample mean and standard deviation of 6.265 and 1.317, respectively.[23]

Columns 1–4 of Table 4 reveal the results from regressions using the historical temperature-volatility measure. In line with theoretical predictions, and despite sample size limitations, Column 1 shows a highly statistically significant hump-shaped relationship between the timing of the Neolithic Revolution and the measure of historical volatility, conditional on mean historical temperature, log-distance to the closest Neolithic frontier, absolute latitude, land area, geographic factors from the exercise of Olsson and Hibbs (2005), and a Europe fixed effect.[24] Moreover, this non-monotonic effect, along with the estimate of optimal volatility, remains qualitatively and quantitatively robust when the specification is modified to use the first principal component of the geographic-endowment variables in Column 2, and when it is further augmented to include controls for elevation, terrain quality, and a landlocked dummy in Columns 3 and 4.[25]

[23] The reader is referred to Tables B.5 and B.6 in Appendix B for additional descriptive statistics and correlations pertaining to this 25-country sample.

[24] Since Olsson and Hibbs (2005) report data on biogeographic endowments – i.e., the numbers of prehistoric domesticable species of plants and animals – at a macroregional level, and because the European continent is treated as one macroregion in their data set, there is hardly any cross-sectional variation in these biogeographic variables within the 25-country sample being considered. As such, controls for biogeographic endowments are omitted from these regressions.

[25] The small island dummy is not considered here since there are no observations in the 25-country sample that are classified as small islands. While the British Isles are included in the sample, the fact that the UK and Ireland share a border prevents the strict qualification of these countries as small island nations. Relaxing this strict definition of a small island nation to treat the UK and Ireland as small islands does not significantly alter the results.

The overall hump-shaped effect of historical temperature volatility on the timing of the Neolithic transition, conditional on the full set of controls in Column 3, is depicted on the scatter plot in Figure 7.[26] To interpret the associated metric effect, a one-degree-Celsius change in historical temperature volatility at the optimal volatility level of 6.392 is associated with a delay in the onset of the Neolithic Revolution by 354 years.

The final four columns of Table 4 repeat the preceding analyses in the same 25-country sample using contemporary temperature volatility, measured as the intertemporal standard deviation of seasonal temperature across 400 observations spanning the 1901–2000 time period. This permits a fair assessment of the identifying assumption that the cross-country distribution of temperature volatility remains stable over long periods of time and therefore that the observed spatial distribution of contemporary temperature volatility may indeed be used to proxy for the unobserved distribution of prehistoric volatility. As is evident from Table 4, and as foreshadowed by the high correlation between the measures of contemporary and historical volatility in Figure 2, the results in Columns 5–8 are strikingly similar to those presented in Columns 1–4, thereby lending further credence to the identifying assumption underlying this exercise. Taken together, these empirical findings provide compelling evidence in support of the proposed theory, suggesting that spatial variation in climatic volatility was indeed a fundamental force behind the differential timing of the adoption of Neolithic agriculture across regions of the world.

4.2 Cross-Archaeological-Site Analysis

Precise estimates of the timing of the agricultural transition are obtained from the radiocarbon dating of archaeological excavations at early Neolithic sites. Thus, while Putterman's (2008) country-level estimates, based on standard archaeological sources and a multitude of country-specific historical references, provide a valuable and, indeed, the only source that covers a large cross-section of countries, this information is undoubtedly a noisy proxy of the actual timing of the Neolithic Revolution. This section supplements the empirical investigation using a novel cross-archaeological-site data set. In particular, local climatic sequences are constructed from grid-cell-level temperature data and combined with high quality data on radiocarbon dates for 750 early Neolithic settlements in Europe and the Middle East to explore the climatic determinants of the timing of the agricultural transition at the site level.

The site-level data on the timing of the Neolithic transition are obtained from the recent data set compiled by Pinhasi, Fort and Ammerman (2005). In constructing their data set, the authors selected the earliest date of Neolithic occupation for each of 750 sites in Europe and the Middle East, using uncalibrated radiocarbon dates that have standard errors of less than 200 radiocarbon years, and omitting all dates with higher error intervals as well as outlier dates. According to the authors, the resulting collection of archaeological sites and the corresponding dates provide a secure sample for the earliest appearance of each of the early Neolithic cultures in the regions covered by the data set. The map in Figure 8 shows the spatial distribution of these archaeological sites.

As in the cross-country analysis, measures of the mean and standard deviation of temperature are constructed from Mitchell et al.'s (2004) monthly time-series temperature data over the 1901–2000 time horizon.[27] Unlike the country-level measures, however, the site-level measures are constructed by averaging

[26] The associated first- and second-order partial effects of historical temperature volatility – i.e., the regression lines corresponding to its first- and second-order coefficients – are depicted in Figures A.5(a)–A.5(b) in Appendix A.

[27] Given that the historical time-series temperature data, used in the cross-country analysis, do not cover all the archaeological sites, the contemporary temperature data are employed instead.

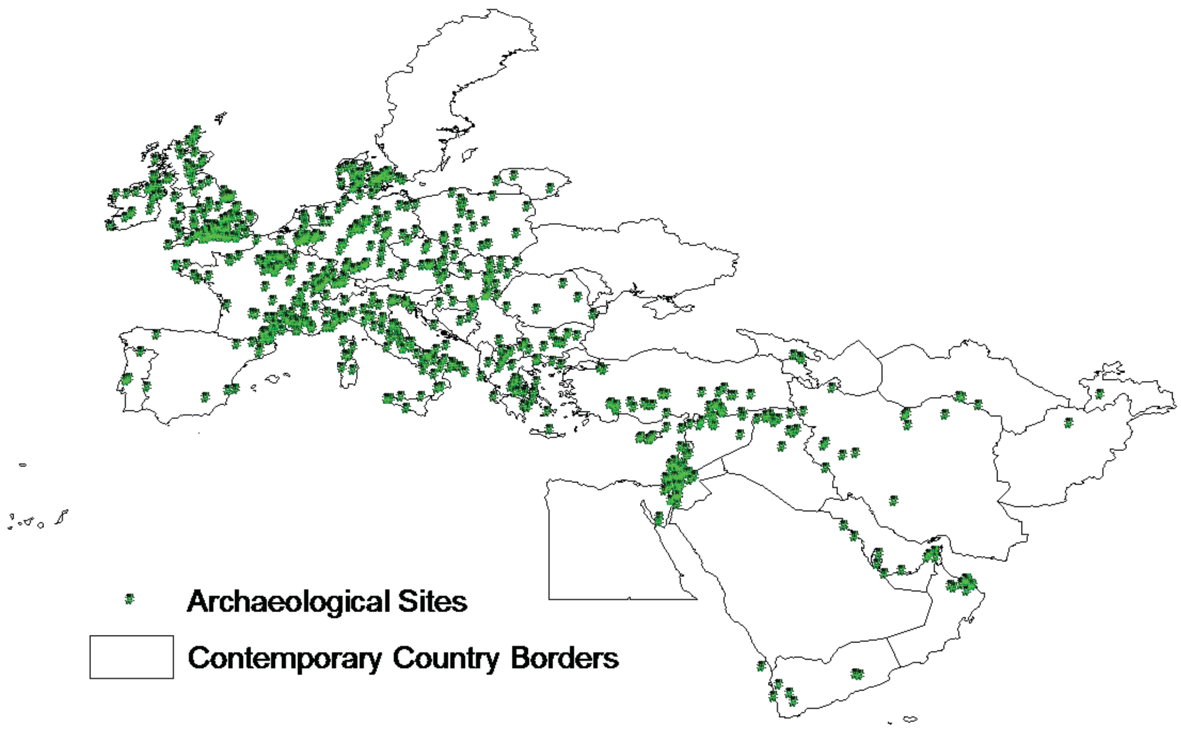


Figure 8: The Spatial Distribution of Neolithic Sites

the grid-cell-level intertemporal moments of temperature across grid cells that fall within a 50-kilometer radius from each site. Thus, temperature volatility for a given site provides a measure of the volatility prevalent in the "average" grid cell within 50 kilometers of the site.

A quadratic specification similar to the one used in the cross-country analysis is employed to test the proposed non-monotonic effect of climatic volatility on the timing of the transition to agriculture across archaeological sites:

$$YST_i = \delta_0 + \delta_1 VOL_i + \delta_2 VOL_i^2 + \delta_3 TMEAN_i + \delta_4 LDIST_i + \delta_5 LAT_i + \delta_6 \Delta_i + \delta_7^{'} \mathbf{\Gamma}_i + \eta_i,$$

where YST_i is the number of thousand years elapsed since the earliest date of Neolithic occupation at site i, as reported by Pinhasi, Fort and Ammerman (2005); VOL_i is the temperature volatility at site i during the contemporary (1901–2000) time horizon; $TMEAN_i$ is the mean temperature (in degrees Celsius) at site i during this time horizon; $LDIST_i$ is the log of the great-circle distance (in kilometers) of site i from Cayönü, one of the Neolithic frontiers identified by Pinhasi, Fort and Ammerman (2005); LAT_i is the absolute latitude (in degrees) of site i; Δ_i is a Europe dummy; $\mathbf{\Gamma}_i$ is a vector of local microgeographic variables, including an index of climatic suitability for heavy-seed cultivation, elevation, and distance to the coast; and, finally, η_i is a site-specific disturbance term.[28] All control variables are site-specific, constructed using grid-cell-level data

[28] The standard errors are clustered at the country level to account for spatial autocorrelation in η_i. Applying the correction method proposed by Conley (1999), however, yields similar results (not reported).

at a 0.5-degree resolution, and aggregated across grid cells located within a 50-kilometer radius of each site.[29] It should also be noted that these sites belong to countries that have identical biogeographic conditions in terms of the numbers of prehistoric domesticable species of plants and animals, according to the data set of Olsson and Hibbs (2005). Hence, the sample considered provides a natural setup to explore whether spatial heterogeneity in climatic sequences generates differences in the timing of the transition to agriculture across regions that have access to common biogeographic endowments.

Table 5 collects the regression results from the cross-archaeological-site analysis. The measure of volatility used in Columns 1 and 2 is the intermonthly standard deviation of temperature over the 1901–2000 time period at the site level (analogous to the country-level volatility measure in Table 1). For the sample of 750 archaeological sites, the volatility measure has a sample mean and standard deviation of 6.264 and 1.416, respectively.[30]

Consistent with the theory, Column 1 of Table 5 shows a statistically significant hump-shaped relationship between the timing of the Neolithic Revolution and temperature volatility, conditional on mean temperature, log-distance to the Neolithic frontier, absolute latitude, and a Europe fixed effect. In particular, the first- and second-order coefficients on temperature volatility are both statistically significant at the 5% level, and they possess their expected signs. The coefficients of interest imply that the optimal level of temperature volatility for the Neolithic transition in this sample of sites is 7.288. It is interesting to note that the magnitude of optimal volatility is very similar to the optimum of 7.167 found for the sample of the 97 countries in Column 8 of Table 1. To interpret the overall metric effect implied by these coefficients, a one-degree-Celsius change in temperature volatility at the optimum is associated with a delay in the onset of the Neolithic Revolution across sites by 50 years.

As for the control variables in Column 1, the significant negative coefficient on log-distance to the Neolithic frontier is consistent with the spatial diffusion of agricultural technology from the frontier, while the coefficient on absolute latitude indicates that, conditional on climatic characteristics, hunter-gatherers at latitudinal bands closer to the poles experienced a delayed onset of farming. Column 2 augments the analysis by introducing site-specific controls for climatic favorability towards agriculture, distance to the sea, and elevation. Consistent with priors, Neolithic sites possessing climatic conditions more suitable for farming underwent an earlier transition, although the point estimate is statistically insignificant. Moreover, the positive coefficient on distance to the sea implies that settlements closer to the coast experienced a later transition to agriculture. To the extent that distance to the coast captures the dependence of prehistoric hunter-gatherers on aquatic resources, this finding is consistent with the archaeological and ethnological record of cultures whose particular subsistence pattern, involving a heavier reliance on aquatic resources, resulted in a delayed adoption of farming.

The remaining columns of Table 5 address the issue of seasonality, discussed previously in the cross-country analysis, by constructing season-specific measures of interannual temperature volatility at the site level (analogous to the country-level volatility measures in Table 2). In particular, for each season-specific volatility measure, two specifications are considered, one with the baseline set of controls (corresponding

[29] The site-level measure of climatic suitability for agriculture is constructed by applying the Olsson and Hibbs (2005) definition of this variable to grid-cell-level data from Kottek et al. (2006) on the global distribution of Köppen-Geiger climate zones. Elevation is calculated using the TerrainBase, release 1.0 data set from the National Oceanic and Atmospheric Administration (NOAA) and U.S. National Geophysical Data Center. Finally, distance to the sea is computed (after omitting the data on lakes) using the "coastlines of seas, oceans, and extremely large lakes" data set (version 3.0) published by Global Mapping International, Colorado Springs, Colorado, USA.

[30] These descriptive statistics along with those of the control variables employed by the analysis are collected in Table B.7 in Appendix B, with the relevant correlations appearing in Table B.8.

Table 5: The Timing of the Neolithic Revolution and Temperature Volatility across Archaeological Sites

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable is Thousand Years Elapsed since the Neolithic Revolution									
	Intertemporal Volatility and Mean of Monthly or Seasonal Temperature (1901–2000) using Observations on:									
	All Months		Spring Seasons		Summer Seasons		Autumn Seasons		Winter Seasons	
Temperature Volatility	0.732**	0.752**	10.086***	9.753***	10.676***	10.286***	12.238***	12.973***	2.453*	2.285
	(0.322)	(0.323)	(2.067)	(2.241)	(3.795)	(3.727)	(1.867)	(2.492)	(1.366)	(1.398)
Temperature Volatility Square	-0.050**	-0.053**	-4.854***	-4.708***	-5.450**	-5.273**	-5.934***	-6.447***	-0.802*	-0.764*
	(0.025)	(0.026)	(1.039)	(1.130)	(2.272)	(2.143)	(1.033)	(1.379)	(0.403)	(0.417)
Mean Temperature	-0.042	-0.025	-0.046	-0.044	0.001	0.006	-0.015	-0.017	-0.038	-0.038
	(0.038)	(0.034)	(0.035)	(0.038)	(0.028)	(0.028)	(0.031)	(0.029)	(0.036)	(0.038)
Log Distance to Frontier	-0.791***	-0.744***	-0.698***	-0.659***	-0.757***	-0.662***	-0.572***	-0.539***	-0.755***	-0.727***
	(0.228)	(0.249)	(0.184)	(0.186)	(0.200)	(0.202)	(0.149)	(0.144)	(0.203)	(0.207)
Absolute Latitude	-0.077***	-0.078***	-0.094***	-0.100***	-0.078***	-0.085***	-0.092***	-0.102***	-0.089***	-0.094***
	(0.021)	(0.022)	(0.017)	(0.020)	(0.018)	(0.022)	(0.017)	(0.023)	(0.013)	(0.019)
Climate		0.148		0.098		0.151		0.084		0.095
		(0.119)		(0.100)		(0.092)		(0.078)		(0.124)
Mean Elevation		0.003		-0.010		-0.002		-0.020		-0.010
		(0.030)		(0.031)		(0.026)		(0.027)		(0.031)
Distance to Coast		0.040		0.030		0.048*		0.055**		0.030
		(0.044)		(0.034)		(0.027)		(0.026)		(0.031)
Europe Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Optimal Temperature Volatility	7.288***	7.029***	1.039***	1.036***	0.979***	0.975***	1.031***	1.006***	1.530***	1.496***
	(0.773)	(0.982)	(0.034)	(0.043)	(0.071)	(0.061)	(0.039)	(0.037)	(0.155)	(0.170)
F-test p-value	0.050	0.055	<0.001	<0.001	<0.001	0.003	<0.001	<0.001	0.093	0.115
Observations	750	750	750	750	750	750	750	750	750	750
Adjusted R^2	0.69	0.69	0.71	0.71	0.70	0.71	0.73	0.73	0.69	0.69
			$\chi^2(1)$ Statistic from Wald Tests of the Null Hypotheses that the Effects of Winter Volatility are not Different from the Effects of:							
			Spring Volatility		Summer Volatility		Autumn Volatility			
Test on the 1st-Order Effect			25.18***	22.94***	6.34**	6.68***	44.06***	30.58***		
			[<0.001]	[<0.001]	[0.012]	[0.010]	[<0.001]	[<0.001]		
Test on the 2nd-Order Effect			25.50***	21.26***	4.94**	5.43**	34.34***	23.03***		
			[<0.001]	[<0.001]	[0.026]	[0.020]	[<0.001]	[<0.001]		

Notes: (i) In Columns 1–2, temperature volatility is the intermonthly standard deviation of monthly temperature across 1,200 observations spanning the 1901–2000 time period, while mean temperature is the intermonthly average across these observations; (ii) In Columns 3–10, temperature volatility is the interannual standard deviation of seasonal temperature across 100 season-specific observations spanning the 1901–2000 time period, while mean temperature is the interannual average across these observations; (iii) For the analyses in Columns 3–10, monthly temperature observations are first aggregated into seasonal ones, and since all sites in the sample appear in the Northern Hemisphere, the seasons are defined as follows: Spring (Mar-Apr-May), Summer (Jun-Jul-Aug), Autumn (Sep-Oct-Nov), Winter (Dec-Jan-Feb); (iv) The excluded regional category in all regressions is the Middle East; (v) The F-test p-value is from the joint significance test of the linear and quadratic terms of temperature volatility; (vi) Heteroskedasticity robust standard error estimates (clustered at the country level) are reported in parentheses below the regression coefficients; (vii) The standard error estimate for the optimal temperature volatility is computed via the delta method; (viii) p-values of the $\chi^2(1)$ statistics are reported in square brackets; (ix) *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

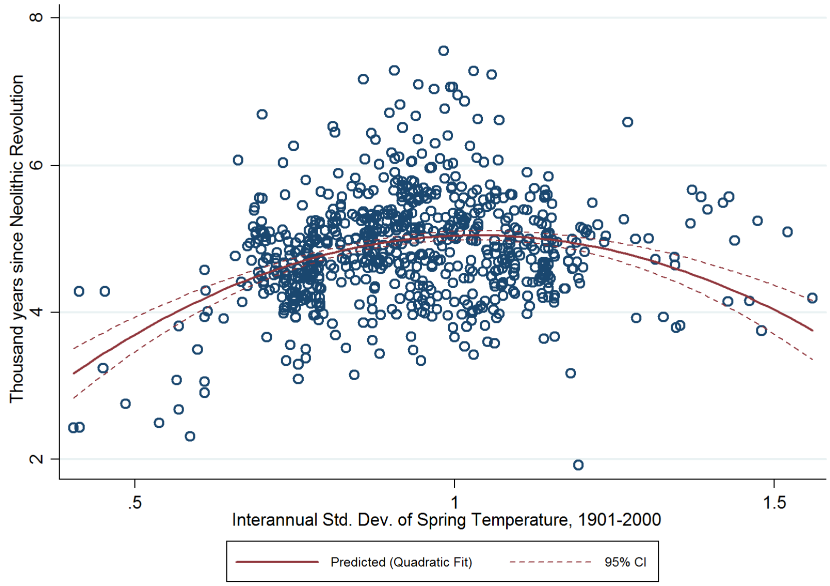


Figure 9: Contemporary Interannual Spring Temperature Volatility vs. the Timing of the Neolithic Revolution across Archaeological Sites

Notes: (i) The depicted relationship reflects a quadratic fit of the relevant data on an "augmented component plus residual" plot (see the discussion in footnote 17 for additional details); (ii) The underlying regression corresponds to the specification examined in Column 4 of Table 5.

to the one from Column 1 of Table 5) and the other with the full set of controls (corresponding to the one from Column 2 of Table 5). As is evident from the table, the regressions generally reveal statistically significant and robust hump-shaped effects of the different season-specific volatility measures on the timing of the Neolithic transition. Specifically, for each season, the estimated first- and second-order coefficients on volatility appear with their expected signs and remain largely stable in magnitude when subjected to the full set of controls for geographic endowments. Note that, consistent with the findings in the cross-country analysis, the impact of winter temperature volatility is quantitatively less important, and incidentally also less precisely estimated, than the effects of the volatility measures for the rest of the seasons. This pattern is more rigorously confirmed by the bottom panel of Table 5, which shows that the effects of winter volatility, as presented in the top panel of the table, differ systematically from the corresponding effects of spring, summer, and autumn volatility, respectively.

To better gauge the quantitative impact of climatic volatility on the advent of farming across sites, consider the following scenario involving spring temperature volatility. Within Germany, the earliest Neolithic site is that of Klein Denkte, possessing a spring volatility of 1.059 and an estimated transition date of 7,930 BP. Note that Klein Denkte's spring volatility is close to the estimated optimum of 1.039, presented in Column 3 of Table 5. On the other hand, the German Neolithic sites of Prenzlau and Kaster both transited to agriculture around 5,500 BP but display significantly different spring volatilities. In particular, Prenzlau has the highest spring volatility within Germany at 1.234, whereas Kaster has one of the lowest at 0.945. Endowing the settlement at Prenzlau with the spring volatility of Klein Denkte would have accelerated the advent of farming in the former by 184 years, whereas the same experiment for Kaster would have given rise to agricultural dependence at this location 41 years earlier. The scatter plot in Figure 9 depicts the overall hump-shaped effect of spring temperature volatility on the timing of the Neolithic transition across archaeological sites, conditional on the full set of controls in Column 4.[31]

In sum, the analysis in this section employed data on the timing of Neolithic settlements in Europe and the Middle East to explore the role of local, site-specific climatic sequences in shaping the transition to farming across reliably excavated and dated archaeological entities. Consistent with theoretical predictions, and in line with the systematic pattern revealed by the cross-country analysis, Neolithic sites endowed with moderate levels of climatic volatility transited earlier into agriculture, conditional on local microgeographic characteristics. The recurrent finding that climatic volatility has had a non-monotonic impact on the emergence of farming, across countries and archaeological sites alike, sheds new light on the climatic origins of the adoption of agriculture.

4.3 Potential Alternative Mechanisms and Additional Robustness Checks

The theory advanced by this research highlights the importance of moderate levels of climatic volatility for instigating transformations in hunter-gatherer subsistence activities, thereby spurring the accumulation of tacit knowledge appropriate for the adoption of farming. Admittedly, however, the reduced-form empirical evidence, while consistent with the proposed theory, could potentially also be reconcilable with alternative mechanisms.

One possibility is that the observed hump-shaped effect of temperature volatility on the timing of the Neolithic Revolution could simply be reflecting the influence of an “ideal agricultural climate,” such that conditions away from this optimum, by increasing the incidence of crop failures, reduce the incentive of hunter-gatherers to adopt farming. There are two statistically related pieces of evidence, however, that mitigate this concern. First, as shown in Table A.1 in Appendix A, while the results from both cross-country and cross-archaeological-site regressions of climatic suitability for agriculture on (a quadratic in) temperature volatility reveal a hump-shaped pattern between these variables, the estimated relationships are generally weak and statistically imprecise. Second, had (high levels of) climatic suitability for agriculture and (intermediate levels of) temperature volatility both been noisy proxies of the true but unobserved “ideal agricultural climate,” with the latter being the less noisy of the two proxies, one should not expect to find a statistically significant positive coefficient on climatic suitability in a specification that regresses the timing of the agricultural transition on both climatic suitability and (a quadratic in) temperature volatility. The results presented in Table 1, however, run contrary to this prediction. Taken together, these findings indicate that climatic suitability for agriculture and (moderate levels of) temperature volatility are not as strongly correlated as priors may suggest and, therefore, that the statistical relationships that these variables possess with the timing of the Neolithic Revolution, conditional on one another, are plausibly reflective of two distinct and independent dimensions of the influence of climate on the adoption of farming.

A second alternative mechanism that could rationalize the reduced-form empirical findings is that of risk diversification across different subsistence strategies. Specifically, if hunter-gatherers happened to possess the prior that agricultural production would mitigate the adverse effects of future climatic shocks on foraging output, then they would have had a strong incentive to adopt farming when the agricultural

[31] The associated first- and second-order partial effects of spring temperature volatility – i.e., the regression lines corresponding to its first- and second-order coefficients – are depicted in Figures A.6(a)–A.6(b) in Appendix A.

technology arrived.[32] Moreover, to the extent that hunter-gatherers in climatically static environments were not likely to have benefited from increased diversification, while those typically facing extreme climatic events might have found agriculture to be unproductive, it follows that farming would have been adopted earlier in locations characterized by moderate climatic shocks.

Given sufficient data on the intertemporal variance-covariance structure of output across prehistoric foraging and farming activities, as well as data on the breadth of the hunter-gatherer dietary spectrum prior to the adoption of agriculture, one could potentially conduct a discriminatory test of the aforementioned risk-diversification mechanism versus the espoused knowledge-accumulation channel – i.e., by assessing their relative importance in mediating the reduced-form hump-shaped effect of climatic volatility on the timing of the Neolithic Revolution. Alternatively, one could exploit data on climatic volatility across different time horizons prior to the onset of agriculture. Since the knowledge-accumulation mechanism emphasizes the deep history of climatic events, whereas the risk-diversification channel highlights expectations of future shocks when farming becomes available for adoption, to the extent that the recent history of climatic fluctuations was more heavily weighted in the formation of such expectations, the relative importance of climatic volatility across longer versus shorter time horizons in explaining the timing of the Neolithic Revolution could potentially reflect the relative significance of these two mechanisms. Unfortunately, the absence of detailed archaeological and prehistoric climatological data makes such tests infeasible at the moment, remaining interesting avenues to explore in future research. Nevertheless, both mechanisms are complementary in highlighting the role of climatic volatility in the adoption of farming.

4.3.1 Accounting for Spatial Dependence across Observations

Setting aside the question of alternative mechanisms, a potentially more germane issue is whether the reduced-form empirical findings can themselves be considered valid, given the statistical assumption of independence of observations in the preceding least-squares regression analyses. Specifically, since farming most likely diffused across space not due to direct technology transfer from the Neolithic frontier but as a result of iterative intermediate adoptions across neighboring societies, and because climatological factors are also known to be strongly correlated across contiguous territories, the estimated effects of temperature volatility on the timing of the agricultural transition could well be both biased and inefficient.

This issue is formally addressed in this section by way of conducting spatial regressions that employ the maximum-likelihood estimator of Drukker, Prucha and Raciborski (2013), which allows for first-order spatial autoregression in both the dependent variable and the disturbance term (SARAR). In particular, the estimated SARAR models are of the form:

$$\begin{aligned} \mathbf{y} &= \lambda \mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u}; \\ \mathbf{u} &= \rho \mathbf{M}\mathbf{u} + \boldsymbol{\epsilon}, \end{aligned}$$

where $\mathbf{y}$ is an $n \times 1$ vector of observations on the dependent variable; $\mathbf{W}$ and $\mathbf{M}$ are $n \times n$ spatial weighting matrices (with diagonal elements equal to zero and off-diagonal elements corresponding to inverse great-circle

[32] While it is unclear how societies with no previous operational experience with farming would come to possess such a prior, the argument that they may have come into frequent contact with early neighboring agriculturalists (and thereby gained the relevant knowledge) leaves open this possibility.

distances between geodesic centroids);[33] $\mathbf{Wy}$ and $\mathbf{Mu}$ are $n \times 1$ vectors representing spatial lags; λ and ρ are non-zero scalar parameters reflecting the spatial autoregressive processes; $\mathbf{X}$ is an $n \times k$ matrix of observations on k independent variables and $\boldsymbol{\beta}$ is its associated $k \times 1$ parameter vector; and finally, $\boldsymbol{\epsilon}$ is an $n \times 1$ vector of residuals. Reassuringly, as revealed in Table A.2 in Appendix A, following this methodology to modify the main empirical specifications from the cross-country and cross-archaeological-site analyses – i.e., allowing for spatial dependence, both in the timing of the Neolithic Revolution and in unobserved heterogeneity, across observations – does not qualitatively alter the key finding of a statistically significant hump-shaped effect of temperature volatility on the timing of the adoption of agriculture.

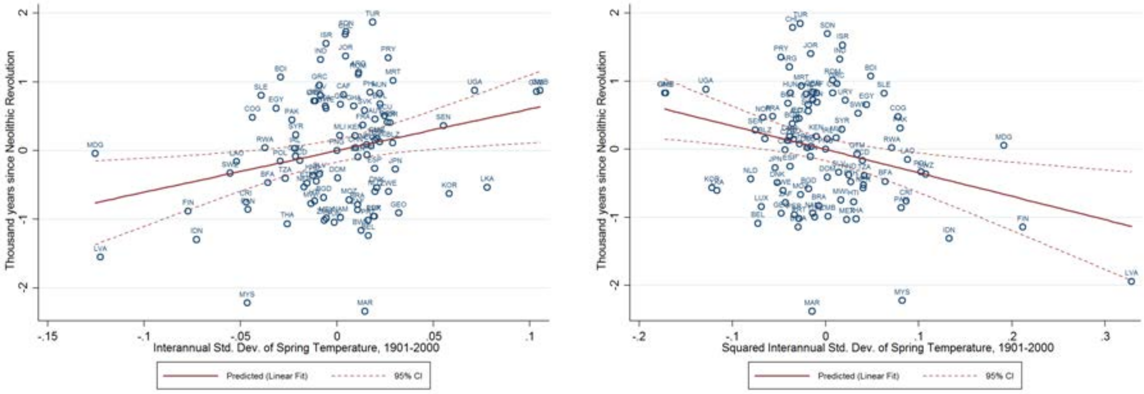
5 Concluding Remarks

This research theoretically and empirically examines the diffusion of agriculture. The theory emphasizes the role of a foraging society's history of climatic shocks in determining the timing of its adoption of farming. It argues that hunter-gatherers facing moderately volatile environments were forced to take advantage of their productive endowments at a faster pace, thereby accumulating tacit knowledge complementary to the adoption of agriculture. Static climatic conditions, on the contrary, by not inducing foragers to exploit the marginal resources available in their habitats, limited the accumulation of such knowledge. Similarly, extreme environmental fluctuations, by drastically altering the resource base and forcing foragers to enact radically different subsistence strategies, delayed the adoption of farming.

The key theoretical prediction regarding a hump-shaped effect of climatic volatility on the adoption of agriculture is empirically demonstrated. Conducting a comprehensive empirical investigation that exploits variations both across countries and across archaeological sites, the analysis establishes that, conditional on biogeographic endowments, climatic volatility has a non-monotonic effect on the timing of the transition to agriculture. Farming was adopted earlier in regions characterized by intermediate levels of climatic volatility, with regions subject to either too high or too low intertemporal variability systematically transiting later. Reassuringly, the results hold at different levels of aggregation and using alternative sources of climatic sequences. The findings are consistent with the proposed theory, suggesting that heterogeneity in climatic volatility was a fundamental force behind the differential timing of the prehistoric transition to agriculture, both at a local and at a global scale.

[33] Employing a contiquity matrix rather than an inverse-distance matrix for the spatial weighting matrices does not qualitatively affect the results of the spatial regressions. The results are also qualitatively insensitive to the truncation of spatial weights (to zero) below various thresholds of inverse distances.

A Supplementary Figures and Results

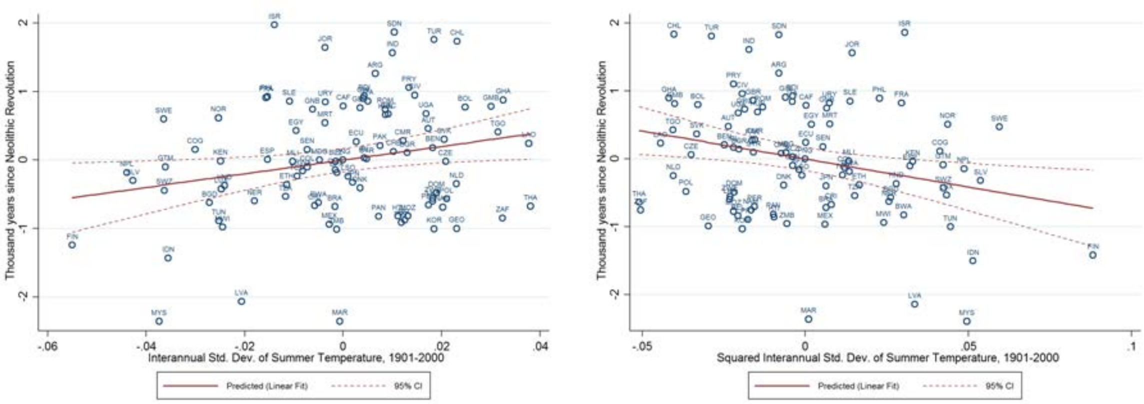


(a) The First-Order Effect

(b) The Second-Order Effect

Figure A.1: The First- and Second-Order Effects of Contemporary Interannual Spring Temperature Volatility

Notes: (i) Each depicted relationship reflects a linear fit of the relevant data on an "added variable" (partial regression) plot; (ii) The underlying regression corresponds to the specification examined in Column 2 of Table 2 in the paper.

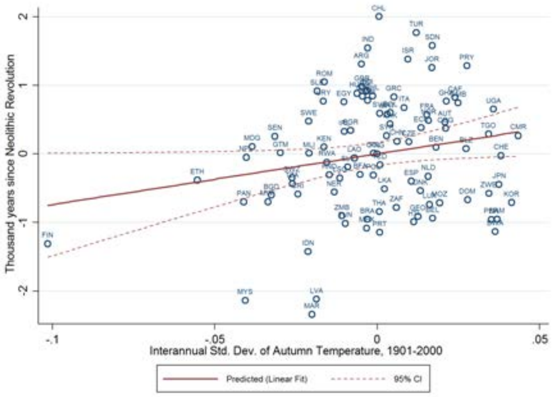


(a) The First-Order Effect

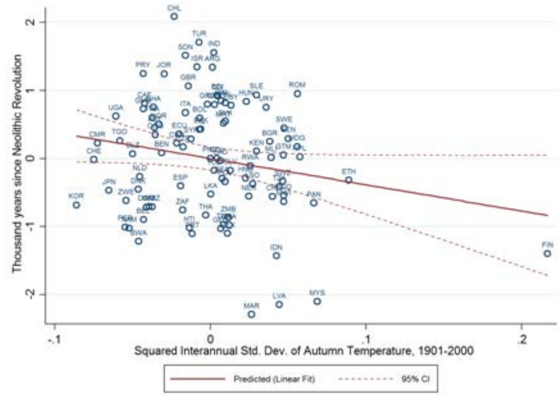
(b) The Second-Order Effect

Figure A.2: The First- and Second-Order Effects of Contemporary Interannual Summer Temperature Volatility

Notes: (i) Each depicted relationship reflects a linear fit of the relevant data on an "added variable" (partial regression) plot; (ii) The underlying regression corresponds to the specification examined in Column 4 of Table 2 in the paper.



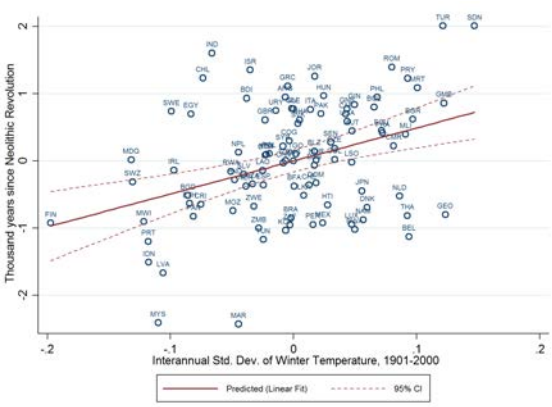
(a) The First-Order Effect



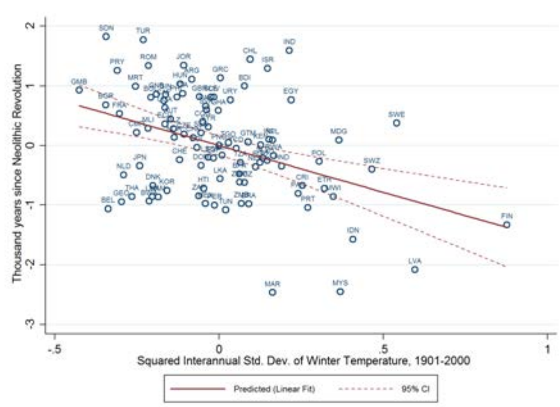
(b) The Second-Order Effect

Figure A.3: The First- and Second-Order Effects of Contemporary Interannual Autumn Temperature Volatility

Notes: (i) Each depicted relationship reflects a linear fit of the relevant data on an "added variable" (partial regression) plot; (ii) The underlying regression corresponds to the specification examined in Column 6 of Table 2 in the paper.



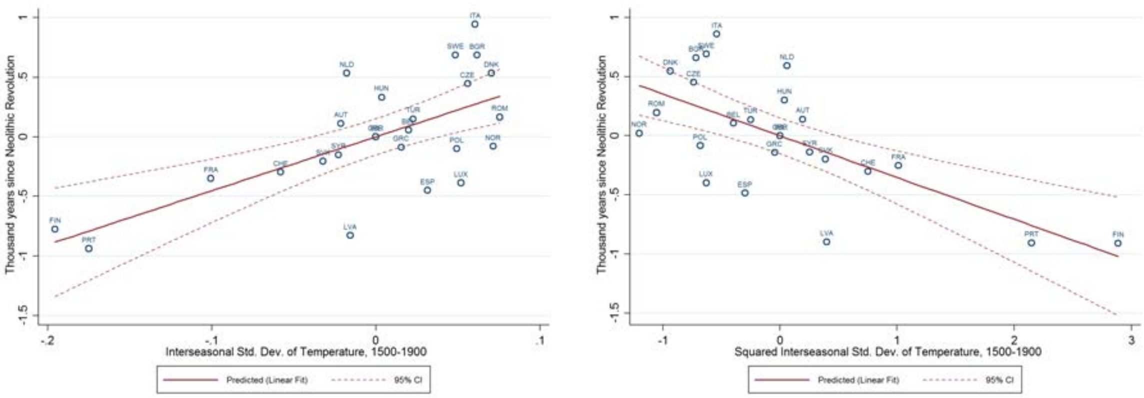
(a) The First-Order Effect



(b) The Second-Order Effect

Figure A.4: The First- and Second-Order Effects of Contemporary Interannual Winter Temperature Volatility

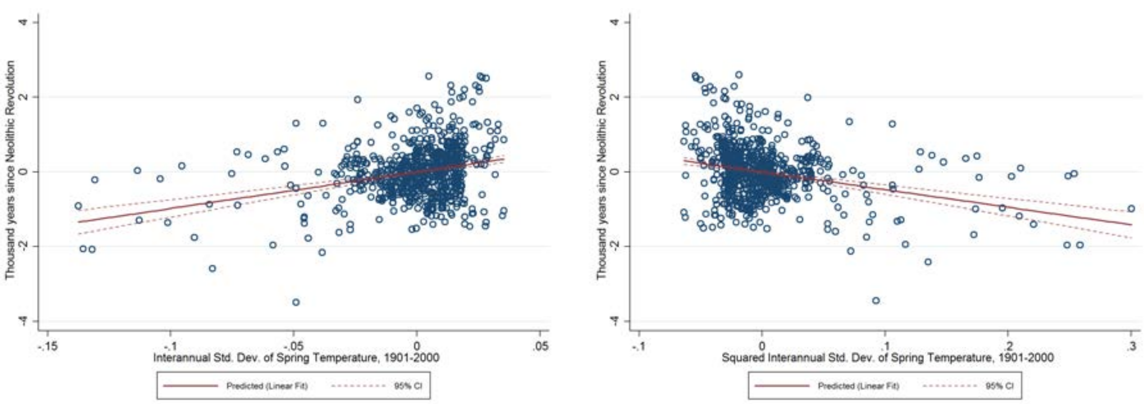
Notes: (i) Each depicted relationship reflects a linear fit of the relevant data on an "added variable" (partial regression) plot; (ii) The underlying regression corresponds to the specification examined in Column 8 of Table 2 in the paper.



(a) The First-Order Effect (b) The Second-Order Effect

Figure A.5: The First- and Second-Order Effects of Historical Interseasonal Temperature Volatility

Notes: (i) Each depicted relationship reflects a linear fit of the relevant data on an "added variable" (partial regression) plot; (ii) The underlying regression corresponds to the specification examined in Column 3 of Table 4 in the paper.



(a) The First-Order Effect (b) The Second-Order Effect

Figure A.6: The First- and Second-Order Effects of Contemporary Interannual Spring Temperature Volatility across Archaeological Sites

Notes: (i) Each depicted relationship reflects a linear fit of the relevant data on an "added variable" (partial regression) plot; (ii) The underlying regression corresponds to the specification examined in Column 4 of Table 5 in the paper.

Table A.1: Climatic Suitability for Agriculture and Temperature Volatility across Countries and Archaeological Sites

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable is the Index of Climatic Suitability for Agriculture									
	Intertemporal Volatility and Mean of Monthly or Seasonal Temperature (1901–2000) using Observations on:									
	All Months		Spring Seasons		Summer Seasons		Autumn Seasons		Winter Seasons	
	Baseline Model	Full Model	Baseline Model	Full Model	Baseline Model	Full Model	Baseline Model	Full Model	Baseline Model	Full Model
	Panel A: Cross-Country Analyses									
Temperature Volatility	0.274	0.910	3.868*	3.300	7.676	7.886	5.783**	5.163	1.389	-1.720
	(0.309)	(0.554)	(2.337)	(3.417)	(4.978)	(7.554)	(2.701)	(4.769)	(1.400)	(2.239)
Temperature Volatility Square	-0.017	-0.091**	-2.649**	-3.072	-5.769	-9.590*	-4.473***	-7.499***	-0.808**	-0.376
	(0.028)	(0.046)	(1.301)	(1.961)	(4.142)	(5.516)	(1.437)	(2.892)	(0.369)	(0.588)
Log Pseudolikelihood	-83.14	-59.94	-80.50	-58.89	-82.64	-57.22	-80.90	-52.10	-80.05	-57.27
Pseudo R^2	0.32	0.51	0.34	0.52	0.32	0.53	0.34	0.57	0.34	0.53
	Panel B: Cross-Archaeological-Site Analyses									
Temperature Volatility	0.055	0.022	1.659	1.558	3.728	2.344	5.986**	4.987**	1.105	1.212*
	(0.289)	(0.296)	(1.669)	(1.742)	(2.817)	(2.918)	(2.273)	(2.108)	(0.697)	(0.687)
Temperature Volatility Square	-0.012	-0.008	-1.371*	-1.291	-2.457	-1.642	-3.899***	-3.269***	-0.464**	-0.422**
	(0.025)	(0.026)	(0.812)	(0.829)	(1.903)	(1.958)	(1.184)	(1.100)	(0.216)	(0.205)
Adjusted R^2	0.70	0.71	0.74	0.74	0.70	0.71	0.73	0.73	0.70	0.71

Notes: (i) For the cross-country analyses (Panel A), given the ordinal nature of the index of climatic suitability for agriculture at the country level, all regressions employ the ordered probit maximum-likelihood estimator, whereas for the cross-archaeological-site analyses (Panel B), all regressions are estimated using the OLS estimator, since the climatic suitability index is a continuous variable at the site level; (ii) For the cross-country analyses (Panel A), the set of control variables in specifications examined in odd-numbered columns respectively correspond to those in Column 1 of Table 1 and in odd-numbered columns of Table 2, whereas the set of control variables in specifications examined in even-numbered columns respectively correspond to those in Column 9 of Table 1 and in even-numbered columns of Table 2; (iii) For the cross-archaeological-site analyses (Panel B), the set of control variables in the specification examined in a given column corresponds to that in the identically numbered column of Table 5; (iv) The regression coefficients associated with control variables are not reported in the interest of saving space and maintaining clarity; (v) Heteroskedasticity robust standard error estimates are reported in parentheses; (vi) For the cross-archaeological-site analyses (Panel B), the standard error estimates are clustered at the country level; (vii) *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table A.2: Robustness to Accounting for Spatial Dependence across Countries and Archaeological Sites

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable is Thousand Years Elapsed since the Neolithic Revolution									
	Intertemporal Volatility and Mean of Monthly or Seasonal Temperature (1901–2000) using Observations on:									
	All Months		Spring Seasons		Summer Seasons		Autumn Seasons		Winter Seasons	
	Baseline Model	Full Model	Baseline Model	Full Model	Baseline Model	Full Model	Baseline Model	Full Model	Baseline Model	Full Model
	Panel A: Cross-Country Analyses									
Temperature Volatility	0.814***	0.665**	5.264**	4.480**	8.736**	8.086**	9.609***	7.409***	1.981	3.139***
	(0.237)	(0.292)	(2.142)	(1.979)	(3.568)	(3.695)	(2.535)	(2.845)	(1.217)	(1.148)
Temperature Volatility Square	-0.061***	-0.057**	-3.312***	-3.432***	-7.122***	-7.274***	-6.304***	-5.156***	-0.905**	-1.206***
	(0.021)	(0.025)	(1.099)	(1.000)	(2.549)	(2.582)	(1.484)	(1.602)	(0.357)	(0.332)
Spatial-Lag AR(1), λ	0.130***	0.085*	0.155***	0.038	0.146***	0.091**	0.126***	0.078*	0.128***	0.051
	(0.044)	(0.046)	(0.044)	(0.044)	(0.044)	(0.045)	(0.043)	(0.044)	(0.048)	(0.047)
Spatial-Error AR(1), ρ	1.024***	1.015***	0.771***	1.024***	1.027***	1.016***	1.032***	1.021***	1.020***	1.021***
	(0.050)	(0.055)	(0.044)	(0.047)	(0.048)	(0.053)	(0.045)	(0.050)	(0.050)	(0.049)
	Panel B: Cross-Archaeological-Site Analyses									
Temperature Volatility	0.703***	0.688***	9.985***	9.734***	11.226***	10.914***	13.258***	14.248***	2.912***	2.830***
	(0.169)	(0.172)	(1.206)	(1.230)	(1.635)	(1.675)	(1.217)	(1.346)	(0.588)	(0.575)
Temperature Volatility Square	-0.047***	-0.045***	-4.840***	-4.723***	-5.788***	-5.610***	-6.609***	-7.263***	-0.889***	-0.927***
	(0.013)	(0.014)	(0.602)	(0.612)	(0.998)	(1.019)	(0.675)	(0.766)	(0.169)	(0.168)
Spatial-Lag AR(1), λ	-0.026***	-0.026***	-0.020**	-0.020**	-0.018*	-0.017*	-0.022**	-0.022**	-0.027***	-0.028***
	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.004)	(0.006)
Spatial-Error AR(1), ρ	0.727***	0.727***	0.370***	0.369***	0.368***	0.367***	0.365***	0.362***	1.160***	0.708***
	(0.033)	(0.034)	(0.024)	(0.024)	(0.024)	(0.024)	(0.026)	(0.027)	(0.024)	(0.035)

Notes: (i) All regressions employ the maximum-likelihood estimator of Drukker, Prucha and Raciborski (2013) that allows for first-order spatial autoregression in both the dependent variable and the disturbance term (SARAR) – i.e., the estimated model is of the form $\mathbf{y} = \lambda\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u}$ with $\mathbf{u} = \rho\mathbf{M}\mathbf{u} + \boldsymbol{\epsilon}$, where $\mathbf{y}$ is an $n \times 1$ vector of observations on the dependent variable, $\mathbf{W}$ and $\mathbf{M}$ are $n \times n$ spatial weighting matrices (with diagonal elements equal to zero and off-diagonal elements corresponding to the inverse great-circle distances between geodesic centroids), $\mathbf{W}\mathbf{y}$ and $\mathbf{M}\mathbf{u}$ are $n \times 1$ vectors representing spatial lags, λ and ρ are non-zero scalar parameters reflecting the spatial autoregressive processes, $\mathbf{X}$ is an $n \times k$ matrix of observations on k independent variables and $\boldsymbol{\beta}$ is its associated $k \times 1$ parameter vector, and finally, $\boldsymbol{\epsilon}$ is an $n \times 1$ vector of residuals; (ii) For the cross-country analyses (Panel A), the specifications examined in odd-numbered columns respectively correspond to those in Column 1 of Table 1 and in odd-numbered columns of Table 2, whereas the specifications examined in even-numbered columns respectively correspond to those in Column 9 of Table 1 and in even-numbered columns of Table 2; (iii) For the cross-archaeological-site analyses (Panel B), the specification examined in a given column corresponds to that in the identically numbered column of Table 5; (iv) The regression coefficients associated with control variables are not reported in the interest of saving space and maintaining clarity; (v) Standard error estimates are reported in parentheses; (vi) For the cross-country analyses (Panel A), the point and standard error estimates of the spatial AR(1) parameters, λ and ρ, are rescaled (divided by 100) to permit reporting of these parameter estimates with greater precision; (vii) *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

B Descriptive Statistics and Correlations

Table B.1: Descriptive Statistics for the 97-Country Sample

		Mean	SD	Min	Max
(1)	Temperature Volatility	3.995	2.700	0.548	10.082
(2)	Mean Temperature	18.751	7.623	0.982	28.194
(3)	Years since Transition	4.516	2.249	1.000	10.500
(4)	Log Distance to Frontier	7.066	2.070	0.000	8.420
(5)	Absolute Latitude	25.170	17.101	1.000	64.000
(6)	Land Area	0.629	1.338	0.003	9.327
(7)	Climate	1.577	1.049	0.000	3.000
(8)	Orientation of Landmass	1.530	0.687	0.500	3.000
(9)	Size of Landmass	30.812	13.594	0.065	44.614
(10)	Geographic Conditions	0.150	1.389	-2.126	2.145
(11)	Domesticable Plants	13.742	13.618	2.000	33.000
(12)	Domesticable Animals	3.845	4.169	0.000	9.000
(13)	Biogeographic Conditions	0.082	1.395	-1.092	1.985
(14)	Mean Elevation	5.767	4.764	0.181	24.897
(15)	Mean Ruggedness	1.217	1.102	0.036	5.474
(16)	% Land in Tropical Zones	0.349	0.414	0.000	1.000
(17)	% Land in Temperate Zones	0.299	0.415	0.000	1.000

Table B.2: Pairwise Correlations for the 97-Country Sample

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	Temperature Volatility	1.000															
(2)	Mean Temperature	-0.790	1.000														
(3)	Years since Transition	0.622	-0.443	1.000													
(4)	Log Distance to Frontier	-0.038	-0.108	-0.220	1.000												
(5)	Absolute Latitude	0.860	-0.899	0.497	0.155	1.000											
(6)	Land Area	0.068	0.026	0.105	-0.292	-0.096	1.000										
(7)	Climate	0.651	-0.717	0.655	0.139	0.748	-0.131	1.000									
(8)	Orientation of Landmass	0.610	-0.545	0.686	-0.014	0.569	-0.050	0.528	1.000								
(9)	Size of Landmass	0.574	-0.413	0.509	0.023	0.431	-0.049	0.361	0.669	1.000							
(10)	Geographic Conditions	0.736	-0.672	0.750	0.053	0.702	-0.090	0.750	0.909	0.812	1.000						
(11)	Domesticable Plants	0.744	-0.731	0.688	0.094	0.832	-0.213	0.826	0.639	0.508	0.791	1.000					
(12)	Domesticable Animals	0.776	-0.726	0.789	0.092	0.794	-0.086	0.809	0.749	0.522	0.841	0.890	1.000				
(13)	Biogeographic Conditions	0.782	-0.749	0.760	0.096	0.836	-0.154	0.841	0.714	0.530	0.840	0.972	0.972	1.000			
(14)	Mean Elevation	0.019	-0.157	0.001	-0.220	-0.145	0.219	-0.140	-0.044	0.120	-0.029	-0.174	-0.124	-0.154	1.000		
(15)	Mean Ruggedness	0.189	-0.349	0.221	0.007	0.174	-0.075	0.188	0.339	0.104	0.267	0.151	0.241	0.202	0.549	1.000	
(16)	% Land in Tropical Zones	-0.796	0.659	-0.414	0.065	-0.735	-0.029	-0.504	-0.323	-0.416	-0.490	-0.582	-0.548	-0.581	-0.166	-0.125	1.000
(17)	% Land in Temperate Zones	0.684	-0.825	0.414	0.197	0.863	-0.163	0.691	0.483	0.343	0.608	0.736	0.689	0.733	-0.204	0.124	-0.609

Table B.3: Descriptive Statistics for the Seasonal Variables

		Mean	SD	Min	Max
(1)	Temperature Volatility for Spring	0.753	0.267	0.308	1.604
(2)	Temperature Volatility for Summer	0.636	0.219	0.328	1.110
(3)	Temperature Volatility for Autumn	0.699	0.267	0.309	1.432
(4)	Temperature Volatility for Winter	0.940	0.548	0.328	2.667
(5)	Mean Temperature for Spring	19.121	8.528	-0.646	31.220
(6)	Mean Temperature for Summer	22.819	4.792	10.601	32.752
(7)	Mean Temperature for Autumn	19.106	7.309	1.565	28.529
(8)	Mean Temperature for Winter	13.952	10.717	-10.035	27.338

Table B.4: Pairwise Correlations for the Seasonal Variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Temperature Volatility for Spring	1.000							
(2)	Temperature Volatility for Summer	0.824	1.000						
(3)	Temperature Volatility for Autumn	0.892	0.924	1.000					
(4)	Temperature Volatility for Winter	0.914	0.838	0.913	1.000				
(5)	Mean Temperature for Spring	-0.716	-0.788	-0.804	-0.806	1.000			
(6)	Mean Temperature for Summer	-0.451	-0.546	-0.548	-0.601	0.880	1.000		
(7)	Mean Temperature for Autumn	-0.711	-0.764	-0.794	-0.808	0.986	0.915	1.000	
(8)	Mean Temperature for Winter	-0.808	-0.832	-0.875	-0.860	0.969	0.775	0.961	1.000
(9)	Years since Transition	0.533	0.476	0.490	0.488	-0.464	-0.198	-0.406	-0.526
(10)	Log Distance to Frontier	-0.002	0.054	0.046	0.046	-0.102	-0.180	-0.122	-0.063
(11)	Absolute Latitude	0.843	0.872	0.892	0.877	-0.900	-0.692	-0.887	-0.929
(12)	Land Area	-0.014	-0.037	-0.037	-0.046	0.043	0.084	0.023	-0.012
(13)	Geographic Conditions	0.684	0.640	0.669	0.715	-0.675	-0.461	-0.653	-0.724
(14)	Biogeographic Conditions	0.753	0.762	0.764	0.765	-0.772	-0.522	-0.722	-0.793
(15)	Mean Elevation	-0.129	-0.117	-0.066	-0.180	-0.126	-0.222	-0.169	-0.133
(16)	Mean Ruggedness	0.078	0.045	0.104	0.049	-0.354	-0.348	-0.343	-0.323
(17)	% Land in Tropical Zones	-0.674	-0.788	-0.787	-0.619	0.648	0.397	0.639	0.747
(18)	% Land in Temperate Zones	0.655	0.750	0.748	0.736	-0.837	-0.706	-0.817	-0.808

Table B.5: Descriptve Statistics for the 25-Country Sample

		Mean	SD	Min	Max
(1)	Hist. Temperature Volatility	6.265	1.317	3.345	8.736
(2)	Hist. Mean Temperature	8.630	4.153	0.978	17.787
(3)	Cont. Temperature Volatility	6.144	1.336	3.258	8.583
(4)	Cont. Mean Temperature	8.911	4.114	0.979	17.831
(5)	Years since Transition	6.492	1.666	3.500	10.500
(6)	Log Distance to Frontier	7.496	1.608	0.000	8.294
(7)	Absolute Latitude	48.927	7.672	35.000	64.000
(8)	Land Area	0.200	0.193	0.003	0.770
(9)	Climate	2.840	0.374	2.000	3.000
(10)	Orientation of Landmass	2.217	0.480	0.500	2.355
(11)	Size of Landmass	41.057	12.310	0.070	44.614
(12)	Geographic Conditions	1.803	0.908	-1.266	2.145
(13)	Mean Elevation	3.879	2.992	0.181	11.784
(14)	Mean Ruggedness	1.374	1.253	0.036	5.017

Table B.6: Pairwise Correlations for the 25-Country Sample

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Hist. Temperature Volatility	1.000												
(2)	Hist. Mean Temperature	-0.336	1.000											
(3)	Cont. Temperature Volatility	0.993	-0.297	1.000										
(4)	Cont. Mean Temperature	-0.344	0.998	-0.313	1.000									
(5)	Years since Transition	0.045	0.781	0.114	0.756	1.000								
(6)	Log Distance to Frontier	-0.269	-0.528	-0.305	-0.513	-0.643	1.000							
(7)	Absolute Latitude	0.186	-0.907	0.144	-0.899	-0.854	0.493	1.000						
(8)	Land Area	0.111	0.059	0.180	0.034	0.376	-0.050	-0.126	1.000					
(9)	Climate	-0.482	0.594	-0.486	0.603	0.299	-0.109	-0.556	-0.259	1.000				
(10)	Orientation of Landmass	0.612	0.006	0.594	0.006	0.220	-0.137	-0.180	0.060	-0.128	1.000			
(11)	Size of Landmass	0.617	0.004	0.599	0.004	0.224	-0.138	-0.179	0.070	-0.129	0.997	1.000		
(12)	Geographic Conditions	0.521	0.125	0.502	0.127	0.284	-0.160	-0.293	0.013	0.073	0.979	0.979	1.000	
(13)	Mean Elevation	0.088	0.109	0.136	0.080	0.446	-0.210	-0.468	0.342	0.085	0.279	0.281	0.299	1.000
(14)	Mean Ruggedness	-0.053	0.022	-0.020	0.000	0.259	0.061	-0.365	0.089	0.058	0.200	0.202	0.214	0.856

Table B.7: Descriptve Statistics for the Cross-Archaeological-Site Sample

		Mean	SD	Min	Max
(1)	Temperature Volatility Overall	6.264	1.416	2.966	10.038
(2)	Temperature Volatility for Spring	0.930	0.172	0.404	1.559
(3)	Temperature Volatility for Summer	0.860	0.133	0.346	1.269
(4)	Temperature Volatility for Autumn	0.925	0.158	0.351	1.285
(5)	Temperature Volatility for Winter	1.411	0.400	0.420	2.566
(6)	Mean Temperature Overall	11.662	4.447	3.764	28.601
(7)	Mean Temperature for Spring	10.680	4.406	2.761	28.198
(8)	Mean Temperature for Summer	19.402	4.775	11.327	35.178
(9)	Mean Temperature for Autumn	12.576	4.783	4.598	28.880
(10)	Mean Temperature for Winter	3.976	4.669	-4.914	23.971
(11)	Years since Transition	6.322	1.279	4.500	10.890
(12)	Log Distance to Frontier	7.615	0.751	0.000	8.329
(13)	Absolute Latitude	44.936	8.365	13.900	58.530
(14)	Climate	2.558	0.868	0.000	3.000
(15)	Mean Elevation	3.997	3.168	0.181	28.719
(16)	Distance to Coast	1.793	1.663	0.093	11.929

Table B.8: Pairwise Correlations for the Cross-Archaeological-Site Sample

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	Temperature Volatility Overall	1.000														
(2)	Temperature Volatility for Spring	0.703	1.000													
(3)	Temperature Volatility for Summer	0.127	0.471	1.000												
(4)	Temperature Volatility for Autumn	0.631	0.797	0.662	1.000											
(5)	Temperature Volatility for Winter	0.631	0.855	0.451	0.750	1.000										
(6)	Mean Temperature Overall	0.043	-0.336	-0.507	-0.477	-0.537	1.000									
(7)	Mean Temperature for Spring	0.064	-0.299	-0.511	-0.452	-0.487	0.989	1.000								
(8)	Mean Temperature for Summer	0.404	-0.065	-0.419	-0.215	-0.273	0.930	0.923	1.000							
(9)	Mean Temperature for Autumn	0.067	-0.316	-0.495	-0.454	-0.530	0.995	0.975	0.934	1.000						
(10)	Mean Temperature for Winter	-0.379	-0.609	-0.515	-0.708	-0.765	0.907	0.882	0.692	0.893	1.000					
(11)	Years since Transition	0.500	0.106	-0.160	0.096	-0.061	0.556	0.539	0.688	0.590	0.303	1.000				
(12)	Log Distance to Frontier	-0.625	-0.236	0.268	-0.117	-0.126	-0.463	-0.434	-0.649	-0.512	-0.168	-0.744	1.000			
(13)	Absolute Latitude	-0.216	0.230	0.420	0.288	0.436	-0.892	-0.896	-0.891	-0.892	-0.728	-0.685	0.545	1.000		
(14)	Climate	-0.108	0.112	0.381	0.329	0.330	-0.756	-0.792	-0.718	-0.742	-0.638	-0.433	0.336	0.752	1.000	
(15)	Mean Elevation	0.454	0.070	-0.041	0.144	0.018	0.182	0.183	0.335	0.199	-0.027	0.499	-0.461	-0.475	-0.207	1.000
(16)	Distance to Coast	0.625	0.515	0.167	0.453	0.550	-0.150	-0.075	0.082	-0.167	-0.413	0.203	-0.240	-0.001	-0.032	0.300

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