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ABSTRACT

Extreme Weather and Long-term Health: Evidence from Two Millennia of Chinese Elites*

Modern technology empowers human beings to cope with various extreme weather events. Using Chinese historical data, we examine the impact of extreme weather on long-term human health in an environment where individuals have no access to modern technology. By combining life course data on 5,000 Chinese elites with historical weather data over the period 1-1840 AD, we find a significant and robust negative impact of droughts in childhood on the longevity of elites. Quantitatively, encountering three years of droughts in childhood reduces an elite's life span by about two years. A remarkably important channel of the childhood drought effect is the deterioration of economic conditions caused by droughts.

JEL Classification: I15, N35

Keywords: longevity, weather, early-life conditions, elites, history of China

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1 Introduction

Extreme weather harms health, though it remains unclear how long the harm may last. Human beings adapt to weather and thus the impact of weather on health attenuates over time. Modern technology provides myriad new means of foraging, clothing, housing, irrigation and migration, all of which empower human beings to cope with extreme weather events. The contemporary health consequences of weather events usually stem from weak institutions, such as inadequate disaster control, lack of capacity for infrastructure repair, poor worker protection, and high barriers to migration. Except for direct casualties (e.g., permanent disabilities), modern weather events rarely damage an individual's lifelong health unless mediated by some institutional failure.

In this study, we turn to historical China in order to understand how extreme weather affected long-term human health when individuals had no access to modern technology. China, as one of the oldest civilizations in the world, remained an agrarian economy until the 1950s. China made little progress in its industrialization until it received technological transfers from the Soviet Union in the Cold War era. Western immigration and trading with Western countries were harshly restricted in China until the First Opium War (1839-1842). In this pre-modern social context, extreme weather episodes recorded by the Chinese Empire's civil servants provide us with a natural experiment setting that is devoid of modern technologies such as air conditioners, heaters, refrigeration, and canned food that mitigate the tyranny of weather.

We examine the longevity of five thousand elites who lived between the year 1 (the first year of the Gregorian calendar) and the year 1840 (the year when Britain forced trade openness in China using a military expedition). The life course data on the elites were originally compiled by Chinese historians in the 20th century as a biographical encyclopedia. The included elites (predominantly male) include high-profile government officials, army generals, monks, artists, writers, poets, and social celebrities. The choice of whom to include in the encyclopedia was made by the historians based on individual prominence in Chinese history. The compiled life course data on elites enable us to calculate their longevity. Further, combining the life course data with historical records of extreme weather events makes it possible to identify the extreme weather episodes encountered by the elites over their lifetime.

Our analysis of the elites' longevity and lifelong exposure to extreme weather events produces four major findings. First and foremost, exposure to droughts in childhood reduced longevity. Quantitatively, having three years of exposure to drought reduced longevity by about two years. In comparison, floods demonstrate a similar but weaker effect, while snow-related disasters and low temperatures show no such effect. Second, early-life economic conditions were an important channel for the childhood drought effect. By merging data on extreme weather with data on historical real GDP per capita for China, we find that the economic output per capita reduced by droughts can explain nearly half of the childhood drought effect on longevity. Third, we find that extreme weather in the two decades prior to an elite's birth also affected his longevity. This extended prenatal effect reflects the importance of economic and health conditions of one generation on the health status of the subsequent generation. Lastly, female elites lived shorter than male elites, but they neither lost nor gained further longevity from extreme weather events in childhood in comparison with male elites.

This study adds to the studies on weather and health, which constitute a burgeoning branch of the new climate-economy literature. The new climate-economy literature, as reviewed by Dell et al. (2014), is concerned with the impact of global climate changes on human welfare. The relationship between climate and health is usually difficult to identify because climate change occurs slowly, perhaps too slowly to generate noticeable impacts over a single generation. Compared with long-term climate trends, weather shocks display more fluctuations, although a solid identification of their impact on human health remains challenging. There are two main challenges to overcome. First, extreme weather events rarely last for a long period of time. Second, human beings are able to adapt to weather patterns such that the long-term and short-term health consequences of weather are disparate. There have been many studies in public health establishing the negative impact of extreme weather on hospitalization outcomes. However, as Deschênes (2014) points out in a survey of this interdisciplinary literature, drawing long-term health implications from those studies would overstate the danger of extreme weather for the general population. Hospitalized patients are more vulnerable to weather shocks than healthy individuals prior to as well as after their hospital admission. Differentiating the long-term effect from the short-term effect is important, and health economists have recently made progress in accounting for adaptive behaviors of human beings in response to weather shocks (Deschênes and Moretti, 2009; Deschênes, Greenstone, and Guryan, 2009; Barreca, 2012; Deschênes and Greenstone, 2011; Graff-Zivin and Neidell, 2014).

Our study builds on documented weather fluctuations but covers a substantially long time period allowing us to speak to climate change. Our data cover a vast number of cohorts who continually adapted to weather shocks occurring in their homeland. Although we cannot directly observe their adaptive behaviors, we find it reasonable to surmise that the potential adaptations were fully exploited because the subjects in our study were the group of individuals who had the most abundant socioeconomic resources available for use in order to survive in hard times. In other words, the childhood drought effect found in our study is a conservative assessment of the health consequence for the general population during the same historical period in China.

Our focus on elites also distinguishes our study from a related literature, which examines the impact of early-life economic conditions on late-life health outcomes. As reviewed by Almond and Currie (2011), Currie and Vogl (2013), Almond, Currie, and Duque (2018), a deprived childhood in nutritional, economic, or social terms has been extensively shown to impair one's health in adulthood. Droughts (Cutler, Miller, and Norton, 2007; Arthi, 2018; Dinkelman, 2017; Duque, Rosales-Rueda, and Sanchez, 2019; Hyland and Russ, 2019), floods (Maccini and Yang, 2009; Comfort, 2016; Abiona, 2017) and famines (Meng and Qian, 2006; van den Berg et al., 2006; Chen and Zhou, 2007; Lumey et al., 2007; van den Berg et al., 2009;

Song, 2010; van den Berg et al., 2016) in childhood have adverse consequences for one's adult health prospects, especially for disadvantaged groups in a society. Our examination of elites has minimized the selection issues. We find that: (1) both droughts and low GDP per capita shorten adult longevity; (2) these two risk factors are positively correlated; and (3) these two risk factors do not have comparable effects on longevity when occurring in later life stages.

In addition, our study contributes to a better understanding of population economics in historical China. China did not start compiling age-specific mortality statistics nationwide until the 1970s (Banister and Preston, 1981). Studies on China's historical population usually relied on genealogies (Lee, Feng, and Campbell, 1994; Zhao, 1997; Shiue, 2016, 2017) or colonist records (Jia, 2014a). We introduce a new data source that features a long time span and a narrow but detailed focus. de la Croix and Licandro (2015), who use the IBN (a biographical database that concentrates on historical Western populations) to examine the relationship between elite longevity and the industrial revolution, argue that the longevity of historical elites is of tremendous importance in the study of economic growth because the human capital of their time was heavily concentrated in them. This argument applies to our context as well. Moreover, the elite class of China was at the center of the millennium-long Chinese imperial regime. Their role as the source of stability and instability in the empire has been recently unraveled (Bai and Jia, 2016).

The rest of the paper is organized as follows. Section 2 provides a description of our data, including its sources and background. In Section 3, we explain our identification strategy. In Section 4, we report our empirical results, including robustness checks, extensions, and a survival analysis. In Section 5, we conclude.

2 Data and Background

Our primary data source is the *Biographical Encyclopedia of Eminent Chinese in History* (BEECH), compiled by Tingcan Liang, Rong Tao, and Shixiong Yu. The BEECH was initially published by Liang in 1927. Since historical events in China were recorded using the lunar calendar, Chinese historians in the past had to conduct calendar conversions in order to use the solar (Gregorian) calendar. Liang unified the formats of birth and death years of eminent persons in Chinese history using the Gregorian calendar. His work traced back to as early as the time of Confucius, who was born in the year 551 BC and died in the year 479 BC. In 1936, Tao and Yu expanded the coverage of Liang's work by conducting further biographic studies. The BEECH has been a standard reference book in the study of Chinese history.

We use the most recent edition of the encyclopedia, published by the National Library of China in 2002, which integrates Liang's original work and Tao and Yu's supplemental works. Henceforth, we refer to this data source as BEECH (2002). A sample page of BEECH (2002) is displayed in Figure A1, where the birth and death years are listed separately for each person. Years are presented in both Chinese monarch format and Gregorian format. For example, Confucius was born in the year *Zhoulingwang 21* (the 21st year under the rule of Monarch *Zhoulingwang*), which is the same as year 551 BC in the Gregorian calendar.

The eminent persons covered in BEECH (2002), or *elites* hereafter, include high-profile government officials, army generals, monks, artists, writers, poets, and social celebrities. In Figure 1, the average longevity of the elites is plotted across the calendar decades in our sample. The average longevity here refers to the average longevity of the elites born in each given decade. We shaded two periods along the time line, one corresponding to the Tang Dynasty and the other to the Yuan Dynasty (which was under the reign of the Mongol Empire). As shown, the Tang dynasty, believed to represent a high point in Chinese civilization, is associated with the longest average longevity across our sample period. In contrast, the Mongols were known to be hostile to Chinese elites, and a decreased average longevity is observed during this period. The figure also displays how the sample size evolves over time. Just as in most historical records (see de la Croix and Licandro (2015) for example), there are more entries in later periods, owing to a mix of increasing population, technological progress in record keeping, and institutional changes that improved vital statistics. The first few years of the sample demonstrate a high average longevity and a small sample size, indicating a stricter sample selection that favors the most long-lived individuals of these early periods. As explained in Section 3, our identification strategy based on within-cohort variations overcomes the potential sample selection issue.

At first glance, one might feel surprised by the long lifespans of the elites across the two-millennial Chinese historical period. A few issues should be noted at this point. First, the longevity reflected in the BEECH (2002) belongs to the elites rather than ordinary Chinese citizens. Traditional medicine was practiced throughout Chinese history, and the elites represented the social class who benefited most from the traditional medicine.[1] Second, the longevity displayed in Figure 1 is in line with case reports. Since China did not start compiling age-specific mortality statistics nationwide until the 1970s (Banister and Preston, 1981), we are unable to corroborate the average elite longevity with large-scale alternative sources. Nevertheless, the average longevity in the figure appears to be reasonable when compared with the numbers reported by historians and demographers in their various works. For example, Tackett (2017) reports that the average lifespan of government ministers in the Song Dynasty of China (from 10th to 13th century) was around 60 years. Similarly, the demographic analysis conducted by Zhao (1997) concludes that the Chinese life expectancy in well-known genealogies varied over a narrow range: 31 years at age 30, and 24 years at age 40.[2] Third and perhaps most importantly, our later estimation controls for cohort fixed effects, such that longevity data with either upward or downward biases do not affect our identification as long as the biases do not vary across individuals within their cohorts. We elaborate on our identification strategy in Section 3.

[1] Needham (1954) notes that the traditional medicine literature in China mentioned a number of advanced concepts in human physiology at an early time, including the circulation system (2nd century), circadian rhythms (2nd century), endocrinology (2nd century), deficiency diseases (3rd century), diabetes (7th century), thyroid hormone (7th century), and immunology (10th century).

[2] de la Croix and Licandro (2015) noted that the average longevity of famous people was about 60 years during the period 1430-1870.

The extreme weather indicators used in our study come from the decadal database compiled by Bai and Kung (2011). Drawing on the original data collected by Zhang et al. (1994) and others, Bai and Kung (2011) compiled the share of years in each decade exposed to four types of extreme weather — droughts, levee breaches, snow-related disasters, and low-temperature calamities (such as frost) — in Chinese history. Hereafter, we refer to the four types of extreme weather events as drought, flood, snow, and low-temperature indicators, respectively. This share-based construction (instead of disaster counts) has an important merit in our context: the shares have automatically adjusted for the variations in record-keeping quality over time. That is, the influence of a year with either over-reported or under-reported disasters on the weather indicators does not go beyond one tenth for the decade to which the year belongs.[3] Figure 2 demonstrates the fluctuations of the four indicators across our sample period.

The summary statistics of the data are reported in Panels A and B of Table 1 (Panel C will be detailed when the related results are discussed). We next discuss the identification strategy of this study.

3 Identification Strategy

Our identification strategy hinges on variations within death cohorts. A death cohort is defined as the set of individuals (elites) who died in the same decade. The decades here refer to, as before, ten-year spans starting with the year whose last digit is zero (such as 1700, 1710, and so on). To illustrate this concept, we draw a diagram in Figure 3, where individuals 1 and 2 both died in decade d and thus belong to the same death cohort. Their respective longevity is represented by two arrows in the figure. Along the time line, each marked segment represents a decade. The first marked segments of both arrows are defined to be the decades of their childhood (*childhood* for short). Notice that the constructed childhoods of the elites

[3] The Bai and Kung (2011) data did not report the counts of extreme weather events. We collect our own weather data and conduct a robustness check using count-based extreme weather indicators in Appendix A.2.

inevitably differ in length because the weather data are available only in calendar decades. Starting from childhood, later calendar decades of an individual are defined as, respectively, the first, second, third, and fourth decades after childhood. They roughly correspond to the teenage, young adult, early middle-age, and middle-age stages in one's life.[4]

In this example, individual 1 has a shorter lifespan than individual 2. With their death decade held the same, the difference in their lifespans comes from their different birth years (i.e., individual 2 has an earlier birth year than individual 1). Their birth years fall into two different calendar decades, to which the historical weather data are matched.[5] As the two individuals differ in their life stages when they appear in a given calendar decade — e.g., individual 2 was in his twenties (i.e., the second decade after childhood) while individual 1 was in his childhood — they encounter different weather patterns over their life stages. We compare the weather patterns at each of their life stages. We formulate this identification strategy as a regression:

$$Longevity_{it} = \sum_{k=0}^{4} W^k_{d(t)}\beta + Z_{it} + \eta_{d(t)} + \epsilon_{it}, \tag{1}$$

where the subscript it as a whole represents individual i who died in year t. The notation it is an index of individual i, but explicitly indicates individual i's death year t for convenience. We denote the calendar decade of year t by $d(t)$. All individuals who died in the same decade belong to the same death cohort. Hence, $\eta_{d(t)}$ represents a death cohort fixed effect. The individuals in a given death cohort d are matched a vector of extreme weather indicator W^k_d, which consists of drought, flood, snow, and low-temperature indicators, in their life stage

[4]An alternative approach to defining childhood and other stages of life is to start with each individual's birth year and let the life decades of different individuals reach the calendar (weather) decade at different times. This approach is equivalent to ours in the sense that each life stage remains matched to the partial decades of the weather data. However, this approach potentially magnifies the inaccuracies in individual birth years.

[5]Their birth years might fall into the same calendar decade and then they are matched with the same calendar decades throughout their life course. In that case, our estimates are conservative in reflecting the weather effects.

$k = 0$ (childhood) to 4 (fourth decade after childhood).[6] Our parameters of interest are the coefficients of the weather indicators, represented by the vector β. Z_{it} denotes a vector of control variables and ϵ_{id} is the error term.

The rationale behind this identification strategy is worth elaborating on. The death cohort fixed effect addresses adverse conditions of a given calendar decade that influence the likelihood of death and thus directly reduce longevity. Such adverse conditions include, but are not limited to, extreme weather events. Extreme weather events, such as floods, may cause death and thus directly affect longevity. The same reasoning applies to diseases and wars. The death-cohort fixed effect ensures that the individuals being compared in terms of longevity have the same life-ending conditions, whether weather-related or not. That is, weather, diseases, wars, or other adversities that may directly cause death are held constant across individuals and thus do not pose a threat to our identification.

The death-cohort fixed effect addresses potential selection issues as well. The difficulty in obtaining elite status varied over time in historical China. In our context, only the elites who died in the same decade are compared with each other in terms of their early-life weather events. These elites can reasonably be assumed to have had climbed up the social hierarchy at the same period in Chinese history. Furthermore, the death-cohort fixed effect overcomes potential sample selection issues in the longevity data. Recall that the average lifespan in Figure 1 appears to be higher when the number of observations is small (e.g., in the first few years of the sample), which suggests that only the most long-lived individuals were recorded. As these heavily selected individuals are compared in this study with each other within their death decades, we do not need to worry about their atypical longevity. In other words,

[6] We consider decades beyond childhood because later life modifiers might be important as well. Life course epidemiology was built on the premise that various biological and social factors throughout life independently, cumulatively and interactively influence health and disease in adult life (Kuh and Ben-Shlomo, 1997). As the number of exposures increase, there might be increasing cumulative damage to biological systems ("accumulation of risk"). This perspective argues for the study of the contribution of early life factors jointly with these later life factors to identify risk and protective processes across the life course.

selectively reported longevity does not affect our identification as long as the selection criteria do not vary across individuals within their cohorts.

4 Empirical Findings

Our empirical findings presented below are divided into four subsections. We start with the baseline results (subsection 4.1) and next discuss robustness (subsection 4.2) and potential channels (subsection 4.3). Then we present two extensions (subsection 4.4). A survival analysis is presented at the end (subsection 4.5).

4.1 Baseline Results

Table 1 reports our benchmark results regarding the effects of extreme weather on the longevity of Chinese elites. We apply the regression specification in equation (1), controlling for individual gender and death-cohort fixed effects, and clustering the standard errors at the birth decade level in all columns.[7] In column (1) of the table, only weather indicators in childhood are included. Weather indicators in subsequent life stages are included sequentially, with column (5) reflecting the full model. Notice that the number of observations decreases as more life stages are added into the regression. This is because not all elites in the sample survived to these later life stages. Drought in childhood has a negative and statistically significant effect on longevity. Quantitatively, for elites that survived to their fourth decade after childhood (i.e., column (5)), an additional year of drought experienced during their childhood decade reduced their longevity by $0.1 \times 6.94 \approx 0.69$ years. Remember that each weather indicator measures the share of years exposed to the associated extreme weather type within a decade. The mean and standard deviation of the drought indicator are, respectively, 0.55 and 0.29 (see Table 1). That is, a one standard deviation increase in drought frequency (2.9 years) in childhood reduces longevity by $0.29 \times 6.94 \approx 2.1$ years. The conversion rate is approximately three (years of exposure) to two (fewer years of life).

[7] Occupations are not provided at the individual level in BEECH (2002).

Floods experienced in childhood also show a negative effect (see Table 2), although it is not always statistically significant across all specifications. This is possibly because the privilege of the elites lay more in their access to economic resources (as detailed later) than in ensuring their own personal safety when exposed to sudden and random extreme weather events. Floods are not only production shocks but may also be fatal in their own right. Elites, if directly killed by floods just as rest of the populace, would not make it into our sample.[8] Quantitatively, take column (5) for example, a one standard deviation increase in the flood frequency (2.1 years, see Table 1) reduces longevity by $0.21 \times 11.54 \approx 2.4$ years. That is, despite occasional statistical insignificance, the conversion rate is 2 (years of exposure) to 2.4 (fewer years of life).

Both drought and flood show occasional statistical significance in later life stages. Notice that drought and flood are not mutually exclusive of each other. They might occur in different locations of China simultaneously. They might also occur in the same location of China at different times within a given year. It is similarly conceivable that they might occur in different locations of China at different times within a decade. In Figure 2 seen previously, there is no clear pattern across the four extreme weather indicators over time. Their exact time and locations are unknown. To account for potential interaction between them, we focus on each weather indicator individually and redo the regression analysis. As shown in Table 3, droughts and floods in childhood show effects comparable to those in Table 2.[9]

In general, we prefer the specifications in Table 2 to those in Table 3, because both drought and flood interact with each other and with other weather patterns as well. For example, temperature is positively correlated with drought, but could be either positively

[8]Selection biases introduced by changes in the distribution of survivors is a major concern in the literature that attempts to link early-life health and long term outcomes, and estimated effects of early-life health shocks may be obscured by mortality selection (Currie and Vogl, 2013). Selective mortality presents an obstacle to detecting a relationship between early-childhood conditions and future outcomes. Although one cannot in general quantify the bias stemming from selective mortality, Bozzoli et al. (2009) show that the bias tends to be largest for health shocks in populations with high baseline mortality rates.

[9]The coefficients of drought and flood indicators in Table 3 are within one standard error of the corresponding coefficients in Table 2, and vice versa.

correlated with flood (through ice melting on mountains) or negatively associated with flood (through evaporation). As we are interested in the unique effect of each type of extreme weather that does not covary with the other three types, the specifications used in Table 2 are our preferred ones which we continue to use hereafter.

4.2 Robustness

We next conduct three robustness checks. First, we divide the sample into three subsamples, respectively corresponding to the first 800 years, the middle 400 years, and the last 600 plus years.[10] We rerun the previous regression using each subsample and report the results in Panel A of Table 4, where three observations emerge. First, the previous childhood and flood effects are found in the most recent subsample. Second, the impact of childhood snow started as being negative but turned positive later. This indicates recent improvements in China's water storage and irrigation technologies. Third, low temperature shows a statistically significant impact in the second earliest subsample (800-1200) but not in other subsamples. These results suggest that all four weather indicators contain sufficient variation to serve as variables of interest. Notice that the occasional statistical (in)significance of the weather-indicator coefficients in some columns do not necessarily mean they have (no) explanatory power. Rather, they relate to the fact that the variation in the four indicators change from time to time, as a result of long-term climate change.

In Panels B to D of Table 4, we report the results from our second robustness check. In this robustness check, we take military conflicts into account. Military conflicts might directly cause the deaths of elites. Extreme weather patterns have been found to result in domestic revolts (Jia, 2014b) and nomadic incursions (Bai and Kung, 2011). The bloodiest massacres in Chinese history occurred during the Anlushan rebellion (755-763), the Mongol conquest of China (1206-1227), the Yuan to Ming dynasty transition (1340-1368), and the Ming to Qing

[10]The choices of the cutoffs also roughly correspond to importance in Chinese history. The power of the aforementioned Tang Dynasty began to decline soon after the year 800. The Mongol Empire started right after the year 1200 (in the year 1206) and the Yuan Dynasty officially started in 1271 when the South Song Dynasty ended.

dynasty transition (1618-1644). Detailed descriptions of these historical events are provided in Appendix A.1. We constructed dummy variables that equal one if an individual was born or died during each of these turbulent periods.[11] Likewise, we include the frequencies of attacks initiated by the nomads and the Chinese against each other.[12] These frequencies were provided in Bai and Kung (2011) at the decade level (the same source as our weather data). Like the previous four dummy variables, the two frequencies can also be linked with both birth and death decades. The birth-year related variables (six in total) are included in Panel B, and the death-year related variables are included in Panel C. Both groups are included in Panel D. Our previous findings continue to hold.

The third robustness check that we conduct is to replace the share-based weather indicators obtained from Bai and Kung (2011) with the drought and flood counts that we collected from alternative source (Song (1992)). We provide the detailed data source and discussion of results in subsection A.2. In general, we find highly similar negative effects of droughts on elite longevity.

4.3 Economic Channel

A natural question emerges as to why extreme weather events in childhood shorten one's lifespan. In this subsection, we examine whether the childhood weather effect operates through an economic channel. In an agrarian economy such as pre-modern China, a negative weather shock reduces agricultural output. GDP changes in turn have an effect on family income and the ability to provide sufficient nutrients, in particular for children. We extract China's real GDP per capita estimates from Broadberry, Guan, and Li (2018), a study of Chinese historical economic performance based on official records in history. There are 59 decades in our sample (including the Northern Song, Ming, and Qing dynasties) that have corresponding estimates in Broadberry et al. (2018). As in our case, their data coverage ends

[11] The regression specification in equation (1) allows variables that vary only with year t to be included.

[12] The attacks initiated by the Chinese on nomads are also considered because the elites in our sample include high-profile army generals.

in the year 1840. In their construction of China's historical economic performance (with GDP per capita of China in 1840 set as the benchmark and at a value of 100), they found that China's real GDP had an upward trend during the 960-1840 period (with gaps), although real GDP per capita (RGDPPC) actually declined over time due to population growth. The summary statistics of their RGDPPC estimates are reported in Panel C of the previous Table 1. In addition, following van den Berg et al. (2006) and van den Berg et al. (2009), we performed a trend/cycle decomposition of the GDP estimates using the Hodrick-Prescott (HP) filter to compile an economic boom indicator (yes=1).[13] In Figure 4, we illustrate the time trend of RGDPPC, with booms indicated.[14]

To examine the channel of the extreme weather effects, we start with regressing RGDPPC on each extreme weather indicator. The standard error is clustered at the dynasty level. We find that an additional drought year in a decade with drought reduces RGDPPC by 1.8 units (recall that the 1840 level is set at 100 units). Other extreme weather indicators are statistically insignificant. We also experiment with using the log of RGDPPC as the dependent variable which allows us to calculate the RGDPPC semi-elasticity. The results indicate that an additional drought year in a decade reduces its RGDPPC by 1.4 percent. The detailed estimates are reported in Panel A of Table 5.

Notice that floods do not show a similar impact on RGDPPC as droughts do. In fact, the flood coefficient is positive (but statistically insignificant). The absence of a flood impact is consistent with our priors. Droughts impact production and may impact population size. Its impact on population size occurs mainly through its impact on production (i.e., causing famines).[15] In comparison, floods also impact both production and population size, but its impact on the latter can be either through its impact on production (i.e., causing famines) or fatalities (i.e., causing direct deaths). Therefore, the impact of floods on per-capita economic

[13]Our HP filter uses a smoothing parameter of 500.

[14]The right-side vertical variable (boom) has only two values 0 and 1, though the axis is labeled with the intermediate values for ease in interpreting the slope. For example, the value 0.8 can be considered as the dawn or dusk of a boom.

[15]Unfortunately, nationwide famine reports are unavailable for our sample period.

performance measures such as RGDPPC is not necessarily negative. The same reasoning applies to results presented in earlier tables where the childhood flood results are found to be less robust than the childhood drought results. That is, if flood directly causes the deaths of some elites (including elites-to-be), those prematurely dead elites would not survive to their later life stages to show a shorter lifespan due to floods.

We next replace the weather indicators in the previous regressions with RGDPPC. The sample is restricted to elites who died in the 59 decades that have corresponding RGDPPC data. We match their life stages to the corresponding RGDPPC data. As before, gender is controlled for in all regressions. We also include dynasty fixed effects to control for technological changes from dynasty to dynasty. As shown in Panel B of Table 5, the RGDPPC in childhood — and almost the only RGDPPC variable — turns out to have a positive and statistically significant effect on longevity, attesting to the existing studies of the impacts of early-life economic conditions on late-life health (Meng and Qian, 2006; van den Berg et al., 2006; Chen and Zhou, 2007; Lumey et al., 2007; van den Berg et al., 2009; Song, 2010; van den Berg et al., 2016). Replacing RGDPPC with the economic boom indicator leads to the same findings, as shown in Panel C of Table 5.[16]

The results in Panel A when taken together with the results in Panels B and C help highlight the effects of weather on longevity through the economic channel. According to the first column in Panel A and the last column in Panel C, a one standard deviation increase in the drought indicator generates a reduction in longevity by $18.47 \times 0.17 \times 0.29 \approx 0.9$ years, which accounts for nearly half of the 2.1 years of reduced longevity illustrated in Table 2. This back-of-the-envelope calculation reveals the importance of the economic channel. A thorough analysis of the economic channel would entail a micro-founded structural model which we do not pursue in this paper.

[16]In this case, significant effects are found in several columns for booms in the second decade after childhood.

4.4 Extensions

We next conduct two further extensions of the previous analysis. The first extension examines extreme weather events prior to an elite's birth. Since our time unit is decade rather than year, we are unable to identify the weather patterns experienced by the elites in utero. However, the long time span of our data makes it possible to examine weather events that occurred even prior to birth, and which of them potentially affected the elites through impacts on their parents. For example, extreme weather events prior to an elite's birth decade are potentially related to the economic conditions of his parents. Adverse economic conditions could lead to poorer health of the parents that results in sub-optimal prenatal conditions, impacting the health of the offspring. The results from the inclusions of decades prior to childhood are reported in Table 6, whose columns follow the structure of Table 2. In this table, the childhood drought effect remains as before (as does the childhood flood effect). More interestingly, droughts prior to childhood also have a negative effect, indicating that negative weather shocks to parents may affect the longevity of their offspring.[17]

Our second extension is concerned with gender inequality. Our previous regressions have all controlled for gender. The number of female elites is small in our sample, accounting for only two percent of the sample (see Table 1). During our sample period, China was a highly patriarchal society and female elites documented in BEECH (2002) were labeled as "talented women" (*cainu* in Chinese), a term that primarily refers to social celebrities with talents in the fine arts (especially painting, music, and poetry). We construct interaction terms between gender (female=1 if the elite is female) and weather indicators by life stage. The results are reported in Table 7. Although female elites turn out to live a substantially shorter life in general (by nearly 20 years), extreme weather events in childhood appear to neither improve nor exacerbate the gender disparity.

[17] The marriage age of females was heavily concentrated at age 20 In historical China (Campbell and Lee, 2010).

4.5 Survival Analysis

In this subsection, we conduct a survival analysis as a complement to the previous analyses that were based on linear regressions. Survival analysis imposes functional form assumptions on the life duration data, and thereby enables researchers to impute the theoretical probability of death along every subject's life course. For example, extreme weather events in childhood may not only shorten longevity by bringing death sooner, but also undermine a subject's health such that his death becomes more likely at every age after childhood. The elevated chances of death at every point in his lifetime can be estimated using survival analysis.

The chance of death and the chance of survival are essentially two sides of the same coin. Technically, the chance of death at a point in time is the probability of death conditional on the fact that the subject is still alive at that point. Likewise, the chance of survival at a point in time is the probability that a living subject continues to live. We first use the Kaplan-Meier estimator, a non-parametric tool in survival analysis, to estimate the survival chances over a lifetime (referred to as a survival function) for various 200-year birth cohorts in our sample. The estimates are presented in Figure 5, where each curve represents the chances (vertical axis) of surviving every age (horizontal axis), with estimates presented separately by cohort. Evidently, the survival chances of the 100-300 AD cohort were far worse at nearly all ages, relative to the cohorts born later. Less than 50 percent of this cohort was expected to survive to age 60. Interestingly, the cohort born between 1500 and 1700 was less likely to survive to age 60 compared to cohorts born during the years 500-700, 900-1100, and 1300-1500. This pattern is consistent with the faltering longevity seen around the year 1700, shown in Figure 1.

We then move on to a parametric Gompertz model. Its hazard function characterizes the aforementioned chance of death over a subject's life course. As a survival analysis counterpart of equation (1), it is specified as

$$h_{it} = \exp\left(\sum_{k=0}^{4} W_{d(t)}^{k}\delta + Z_{it} + \eta_{d(t)} + \gamma t\right), \tag{2}$$

where γ is a new parameter to be estimated, which captures how the hazard of death evolves along a subject's life course (where an estimated $\hat{\gamma} > 1$ indicates an accelerated death hazard). Other parameters and variables in equation (2) are similar to those in equation (1) and our primary interest remains in the coefficient vector δ. Here, a positive coefficient of an extreme weather indicator implies a higher hazard of death at all ages. The hazard function is estimated using the maximum likelihood method, and we cluster the standard errors at the birth cohort decade as before.

The regression results are reported in Table 8. Both drought and flood in childhood raise the hazard of death significantly. Unlike in Table 2, the magnitudes of the coefficients here cannot be directly linked to extra years of life. Rather, through survival analysis, we can instead compute expected life spans (longevity) with the estimated coefficients and data *for each individual*. Take column (5), for example. The median survival time of the elites who did not get exposed to drought in childhood is 68.4 years, while that of the elites who experienced drought in childhood is 66.0 years. The difference, namely 2.4 years, is quite close to what the linear regression (column (5), Table 1) implies. For flood exposure in childhood, the two median survival times are 65.8 years and 66.8 years, respectively. The difference of 1.0 year is shorter than the difference implied by the linear regression.

Just as with the non-parametric estimates in Figure 5, the parametric estimates can also help provide an estimate of the chances of surviving at every age. With the estimates from column (5) of Table 8, we compute the survival chances with and without childhood exposure to each type of extreme weather. The survival chance loci are displayed in Figure 6. Both droughts and floods appear to make a remarkable difference to the survival estimates for elites at nearly all ages.[18]

[18] The difference is minimal in childhood since that is when the extreme weather occurs. It is also minimal at much older ages because natural deaths occur at those ages.

5 Concluding Discussion

Modern technology enables humans to cope with extreme weather. In this paper, we turn to a pre-modern society to assess how extreme weather events impacted human health in the absence of technologies that can help humans adapt to weather. A long period of Chinese history spanning two millennia allows us to combine life course data on 5,000 elites with historical weather series data to identify the impact of extreme weather events experienced early in life on subsequent longevity. Droughts in childhood are found to have a negative impact on longevity. Encountering three more years of drought reduced an elite's lifespan by about two years. Economic conditions are an important channel of this childhood drought effect. Flood in childhood has a similar but lesser effect, possibly because the privilege of elites lay more in their access to economic resources rather than an ability to ensure their own personal safety when exposed to unexpected extreme weather. Floods are not only output shocks but are also population shocks (fatal in their own right). Elites, if directly killed by floods similar to the rest of the populace, would not make it into our sample.

The childhood weather effect found here is a conservative count of how extreme weather impacts human health for two reasons. First, relative to the general population, elites were the most privileged and the socioeconomic group with the least exposure to extreme weather during their lifetimes. Second, our knowledge of the extreme weather events encountered by the elites is limited to the decades of their occurrences. Without knowing the precise location and time of the extreme weather events, our extreme weather indicators tend to *overstate* the relevance of extreme weather on human longevity. This results in *underestimated* impacts of extreme weather. Put differently, an elite in our sample might live at a time/location that was, despite being matched with the weather events in the dataset, unaffected by the recorded weather events. This data limitation actually points to a direction for future research, which is to collect more precise (in terms of both time and location) data on extreme weather incidents and match them to the locations of the elites over their life courses. BEECH (2002) does not provide the residence locations of the elites. However, it was compiled as a biographic encyclopedia that can be linked to various other biographic records of the elites. Assembling weather trajectories of the elites over their lifetimes will shed more light on how elites adapted to, or failed to adapt, extreme weather.

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Figure 1: Overview of the Longevity Data

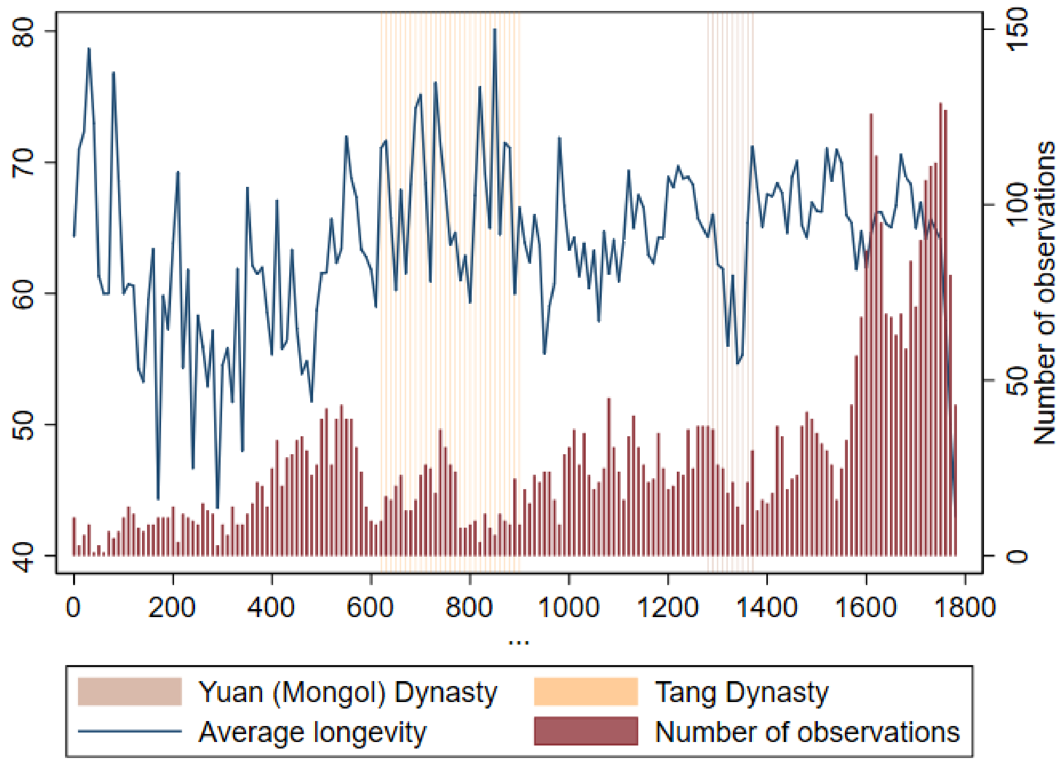

Figure 2: Weather over the 1800 Years

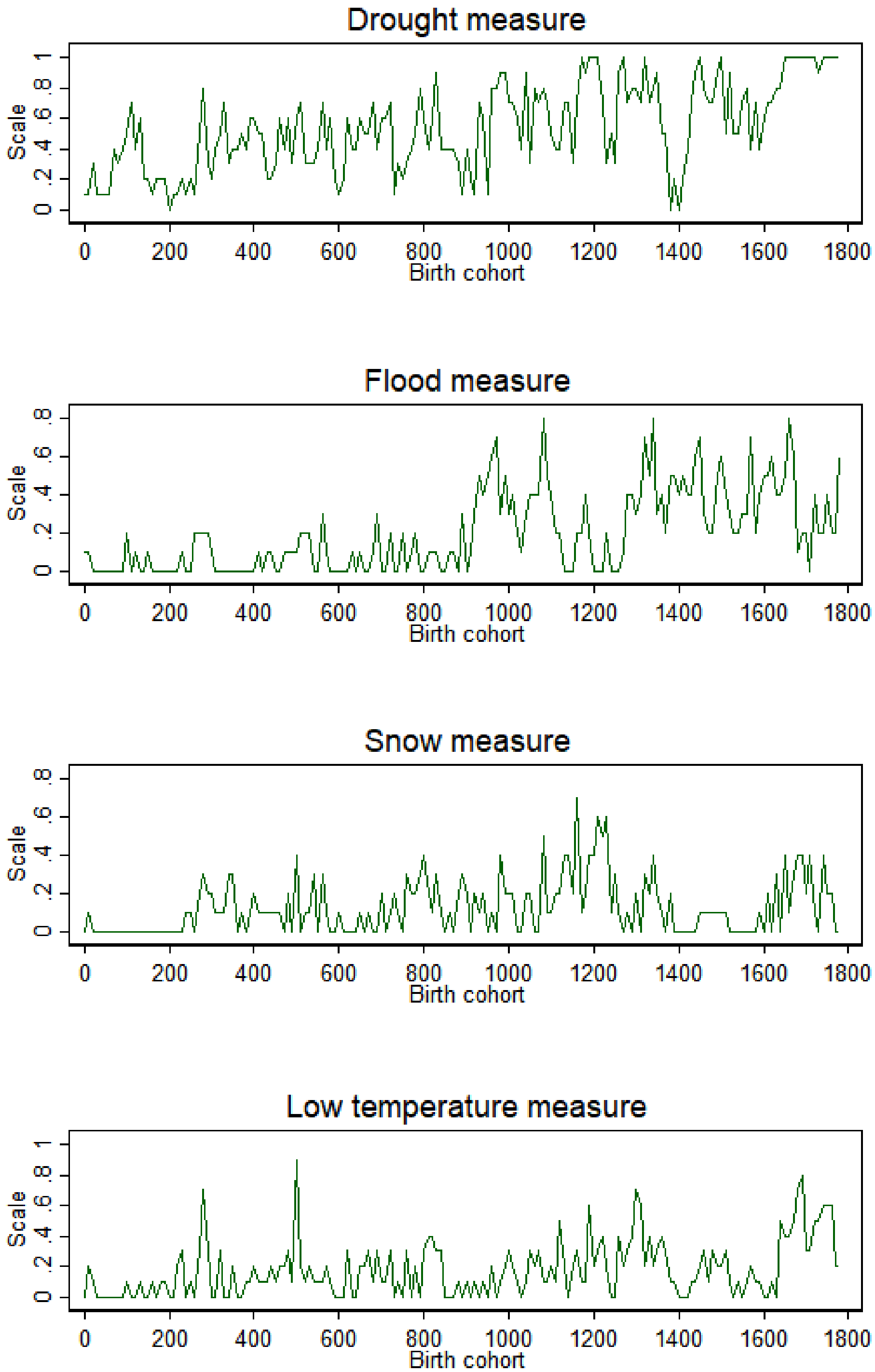

Figure 3: Regression and Identification

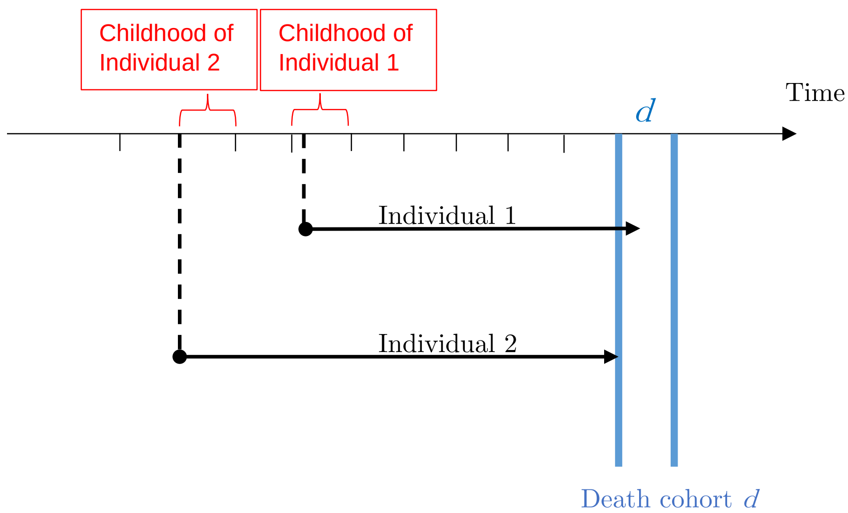

Figure 4: GDP per capita and Weather

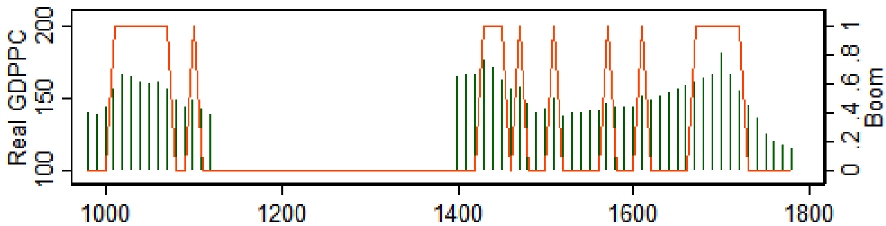

Figure 5: Survival Function Estimates

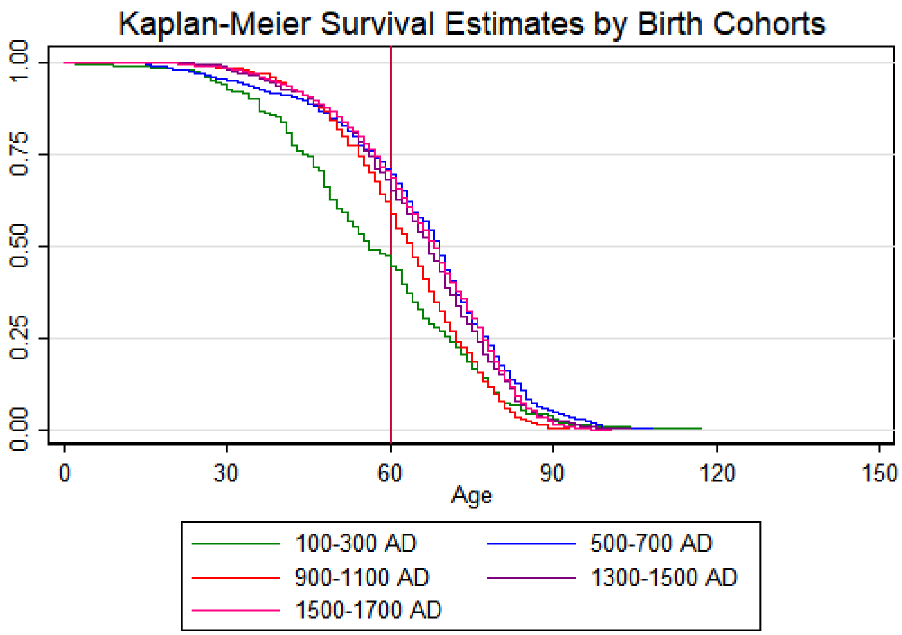

Figure 6: Survival Patterns by Childhood Weather

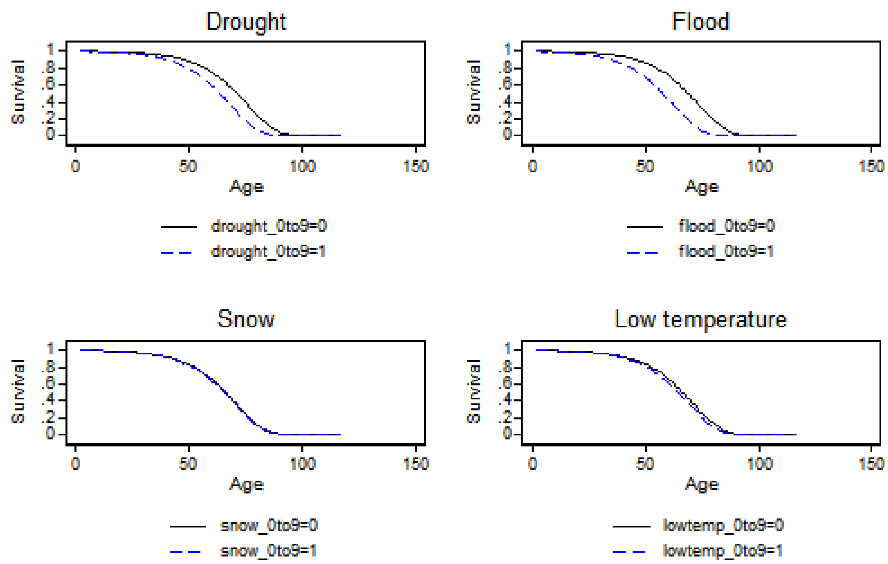

Table 1: Summary Statistics

Variable	Observations	Mean	Std.	Min.	Max.
Panel A: The longevity data §					
Birth decade	5,114	119.26	50.49	0	181
Gender (female=1)	5,114	0.02	0.12	0	1
Longevity	5,114	63.77	15.63	2	117
Panel B: The weather data †					
Drought	184	0.55	0.29	0	1
Flood	184	0.20	0.21	0	0.8
Snow	184	0.13	0.14	0	0.7
Low temperature	184	0.18	0.19	0	0.9
Panel C: The economic data †					
Real GDP per capita	59	146.65	18.25	99.6	181.7
Boom (yes=1)	59	0.39	0.49	0	1

§ Decade 0 refers to years 1 to 9 (AD), while decade 181 refers to years 1810 to 1819 (AD). All individuals in the data had died by the year 1840. † The data are decadal (each observation here corresponds to a calendar decade).

Table 2: Benchmark Results

	(1)	(2)	(3)	(4)	(5)
Dep. Variable is longevity (in years)					
▼*Childhood*.					
Drought in childhood	-8.55**	-6.72**	-6.21*	-6.77**	-6.94*
	(3.51)	(3.34)	(3.33)	(3.33)	(3.93)
Flood in childhood	-8.18	-7.18	-10.13*	-10.17*	-11.54**
	(5.18)	(5.05)	(5.73)	(5.73)	(5.81)
Snow in childhood	2.85	4.34	1.54	0.28	1.55
	(4.17)	(5.10)	(5.04)	(5.64)	(5.54)
Low temp. in childhood	0.16	0.18	-0.45	-0.62	-2.49
	(4.96)	(4.56)	(4.61)	(4.91)	(5.15)
▼*Teenage*.					
Drought in 1st decade after childhood		-6.12*	-3.95	-3.20	-3.56
		(3.34)	(3.21)	(3.30)	(3.55)
Flood in 1st decade after childhood		-9.08*	-7.94*	-8.94*	-8.24
		(4.79)	(4.56)	(5.13)	(5.40)
Snow in 1st decade after childhood		4.73	4.67	3.09	3.98
		(4.86)	(5.93)	(6.37)	(6.72)
Low temp. in 1st decade after childhood		-1.40	-0.81	-0.65	-1.64
		(4.61)	(4.34)	(4.66)	(5.10)
▼ *Young age*.					
Drought in 2nd decade after childhood			-5.69*	-5.05	-5.05
			(3.32)	(3.24)	(3.60)
Flood in 2nd decade after childhood			-9.80**	-9.56**	-12.62**
			(4.91)	(4.80)	(5.43)
Snow in 2nd decade after childhood			2.95	0.98	-0.12
			(4.66)	(6.15)	(6.81)
Low temp. in 2nd decade after childhood			-1.98	-0.20	-1.46
			(4.76)	(4.81)	(5.44)
▼ *Middle age I*.					
Drought in 3rd decade after childhood				-4.88	-3.60
				(3.23)	(3.34)
Flood in 3rd decade after childhood				-3.32	-3.09
				(5.04)	(4.85)
Snow in 3rd decade after childhood				-3.68	-2.87
				(4.82)	(6.11)
Low temp. in 3rd decade after childhood				-0.21	1.53
				(4.83)	(5.29)
▼ *Middle age II*.					
Drought in 4th decade after childhood					-5.93*
					(3.45)
Flood in 4th decade after childhood					-2.81
					(4.78)
Snow in 4th decade after childhood					4.43
					(5.19)
Low temp. in 4th decade after childhood					-3.53
					(5.10)
Observations	5,114	5,114	5,114	5,112	5,102
R-squared	0.14	0.15	0.16	0.16	0.17

Death decade and gender fixed effects are included. Robust standard errors in parentheses, clustered at the birth decade level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Each Weather Indicator Separated Out

	(1)	(2)	(3)	(4)
Dep. Variable is longevity (in years)				
Drought in childhood	-9.93***			
	(3.20)			
Drought in 1st decade after childhood	-7.10**			
	(3.08)			
Drought in 2nd decade after childhood	-6.97**			
	(3.04)			
Drought in 3rd decade after childhood	-5.89*			
	(3.20)			
Drought in 4th decade after childhood	-6.10*			
	(3.59)			
Flood in childhood		-12.09**		
		(5.50)		
Flood in 1st decade after childhood		-11.70**		
		(5.11)		
Flood in 2nd decade after childhood		-13.88***		
		(5.22)		
Flood in 3rd decade after childhood		-4.76		
		(4.42)		
Flood in 4th decade after childhood		-3.33		
		(4.67)		
Snow in childhood			2.30	
			(6.23)	
Snow in 1st decade after childhood			2.47	
			(7.10)	
Snow in 2nd decade after childhood			-4.72	
			(6.99)	
Snow in 3rd decade after childhood			-9.78	
			(6.61)	
Snow in 4th decade after childhood			-4.83	
			(5.05)	
Low temp. in childhood				-2.25
				(5.64)
Low temp. in 1st decade after childhood				-3.54
				(5.93)
Low temp. in 2nd decade after childhood				-7.31
				(5.66)
Low temp. in 3rd decade after childhood				-4.86
				(4.73)
Low temp. in 4th decade after childhood				-6.99
				(4.79)
Observations	5,102	5,102	5,102	5,102
R-squared	0.15	0.16	0.13	0.14

Death decade and gender fixed effects are included. Robust standard errors in parentheses, clustered at the birth decade level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Robustness Checks

Panel A: By time periods

Period:	Years after 1200	Years 800 to 1200	Years before 800
Drought in childhood	-14.88**	9.06	1.65
	(6.30)	(6.75)	(8.26)
Flood in childhood	-17.14**	-11.63	-8.14
	(7.74)	(8.91)	(16.51)
Snow in childhood	4.20	-12.92	-24.92*
	(8.55)	(10.51)	(13.87)
Low temp. in childhood	-5.02	-25.76*	6.80
	(6.45)	(14.85)	(12.62)
Observations	3,054	820	1,228
R-squared	0.21	0.29	0.22

Panel B: Control for wars at birth

Specification:	Col. (1) in Table 2	Col. (2) in Table 2	Col. (3) in Table 2	Col. (4) in Table 2	Col. (5) in Table 2
Drought in childhood	-9.99***	-7.52**	-7.72**	-7.95**	-7.90**
	(3.67)	(3.45)	(3.49)	(3.52)	(3.99)
Flood in childhood	-5.58	-4.49	-7.27	-7.42	-8.66*
	(4.97)	(4.75)	(5.17)	(5.23)	(5.17)
Snow in childhood	4.63	6.23	4.23	3.40	4.05
	(4.31)	(5.30)	(5.02)	(5.42)	(5.33)
Low temp. in childhood	-0.22	-0.84	-0.79	-0.89	-2.51
	(4.87)	(4.26)	(4.42)	(4.70)	(4.84)
Observations	5,114	5,114	5,114	5,112	5,102
R-squared	0.16	0.17	0.18	0.18	0.19

Panel C: Control for wars at death

Specification:			<As above>		
Drought in childhood	-9.97***	-7.92**	-8.01**	-8.38**	-8.24**
	(3.67)	(3.45)	(3.52)	(3.55)	(4.02)
Flood in childhood	-5.97	-4.91	-7.68	-7.81	-9.23*
	(5.05)	(4.95)	(5.45)	(5.52)	(5.52)
Snow in childhood	4.90	6.67	4.43	3.27	3.94
	(4.28)	(5.23)	(5.08)	(5.54)	(5.47)
Low temp. in childhood	0.31	0.15	-0.10	-0.10	-1.87
	(4.85)	(4.32)	(4.50)	(4.81)	(5.00)
Observations	5,114	5,114	5,114	5,112	5,102
R-squared	0.16	0.17	0.18	0.18	0.18

Panel D: Control for wars at birth and death

Specification:			<As above>		
Drought in childhood	-10.10***	-7.61**	-7.81**	-8.03**	-7.99**
	(3.67)	(3.44)	(3.49)	(3.52)	(4.00)
Flood in childhood	-5.43	-4.34	-7.11	-7.26	-8.52
	(4.97)	(4.75)	(5.17)	(5.24)	(5.17)
Snow in childhood	4.68	6.36	4.39	3.57	4.19
	(4.31)	(5.30)	(5.04)	(5.44)	(5.36)
Low temp. in childhood	-0.19	-0.88	-0.84	-0.93	-2.56
	(4.87)	(4.27)	(4.43)	(4.71)	(4.85)
Observations	5,114	5,114	5,114	5,112	5,102
R-squared	0.16	0.18	0.18	0.18	0.19

Dep. Variable is longevity (in years). Death decade and gender fixed effects are included. Robust standard errors in parentheses, clustered at the birth decade level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: The Economic Channel of the Childhood Weather Effect

Panel A: Weather and RGDPPC								
Dep. Variable:	RGDPPC				ln(RGDPPC)			
Drought	-18.47**				-0.14**			
	(5.26)				(0.04)			
Flood		11.01				0.09		
		(8.98)				(0.06)		
Snow			4.46				0.03	
			(25.25)				(0.18)	
Low temp.				-15.46				-0.12*
				(6.83)				(0.05)
Observations	59	59	59	59	59	59	59	59
R-squared	0.06	0.01	0.00	0.03	0.07	0.02	0.00	0.04
Panel B: RGDPPC over life course								
RGDPPC, childhood			0.21***	0.14*	0.16**	0.17**	0.17*	
			(0.05)	(0.08)	(0.08)	(0.08)	(0.08)	
RGDPPC, 1st decade after childhood				0.08	-0.05	-0.03	-0.05	
				(0.06)	(0.07)	(0.07)	(0.08)	
RGDPPC, 2nd decade after childhood					0.11*	0.02	0.03	
					(0.06)	(0.07)	(0.07)	
RGDPPC, 3rd decade after childhood						0.07	0.04	
						(0.05)	(0.08)	
RGDPPC, 4th decade after childhood							0.03	
							(0.05)	
Observations			2,797	2,763	2,747	2,721	2,680	
R-squared			0.10	0.10	0.10	0.10	0.09	
Panel C: Economic booms over life course								
Boom (=1), childhood			2.71**	2.01*	1.95*	1.91*	1.99*	
			(1.26)	(1.09)	(1.00)	(1.01)	(1.02)	
Boom (=1), 1st decade after childhood				2.36*	1.45	1.50	0.77	
				(1.24)	(1.14)	(1.18)	(1.08)	
Boom (=1), 2nd decade after childhood					2.46**	2.41**	3.19**	
					(1.13)	(1.18)	(1.20)	
Boom (=1), 3rd decade after childhood						0.23	1.23	
						(1.49)	(1.62)	
Boom (=1), 4th decade after childhood							-1.27	
							(1.77)	
Observations			2,797	2,763	2,747	2,721	2,680	
R-squared			0.06	0.06	0.07	0.06	0.06	

RGDPPC is the abbreviation of real GDP per capita. In Panel A: robust standard errors are reported in parentheses, clustered at the dynasty level. In Panel C, only the decades with RGDPPC data are included (59 in total, see text for details). In Panels B and C: dep. variable is longevity (in years); dynasty and gender fixed effects are included; robust standard errors are reported in parentheses, clustered at the birth decade level. In all panels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Prior to Birth Weather

	(1)	(2)	(3)	(4)	(5)
Dep. Variable is longevity (in years)					
Drought in childhood	-8.72**	-6.23*	-6.78*	-7.58**	-7.97*
	(3.64)	(3.34)	(3.55)	(3.62)	(4.53)
Flood in childhood	-8.47	-7.42	-10.86*	-10.01*	-13.37**
	(5.28)	(5.23)	(5.60)	(5.66)	(5.78)
Snow in childhood	6.91	7.83	5.25	4.27	6.73
	(5.90)	(6.79)	(7.15)	(7.53)	(7.20)
Low temp. in childhood	-0.03	0.52	1.05	1.12	-2.96
	(5.18)	(5.08)	(5.51)	(5.75)	(6.09)
Weather indicators in later life	None	Till teenage	Till 20s	Till 30s	Till 40s
Drought in 1st decade before childhood	-3.77	-3.83	-5.02	-6.84	-8.54*
	(3.30)	(3.49)	(3.48)	(4.41)	(4.44)
Flood in 1st decade before childhood	-0.92	-3.94	-2.62	-3.40	-3.00
	(5.22)	(5.32)	(5.22)	(5.23)	(6.06)
Snow in 1st decade before childhood	6.92	3.46	2.57	3.59	5.28
	(6.18)	(6.30)	(6.49)	(6.24)	(6.40)
Low temp. in 1st decade before childhood	-2.04	-2.84	-1.94	-2.33	-0.71
	(4.51)	(4.72)	(5.07)	(5.27)	(5.15)
Drought in 2nd decade before childhood	-3.99	-5.48*	-6.77*	-7.94**	-6.44*
	(3.38)	(3.30)	(3.80)	(3.74)	(3.83)
Flood in 2nd decade before childhood	-3.54	-2.67	-5.20	-3.13	-3.38
	(5.30)	(5.01)	(4.93)	(5.76)	(5.46)
Snow in 2nd decade before childhood	-0.79	-2.16	-0.82	-0.75	-4.07
	(5.20)	(5.48)	(5.41)	(5.12)	(5.39)
Low temp. in 2nd decade before childhood	-5.78	-4.73	-5.77	-5.08	-9.97*
	(4.58)	(5.05)	(5.20)	(5.49)	(5.79)
Observations	5,114	5,114	5,114	5,112	5,102
R-squared	0.15	0.16	0.18	0.18	0.19

Death decade and gender fixed effects are included. Robust standard errors in parentheses, clustered at the birth decade level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Childhood and Weather: Gender Difference

Dep. Variable is longevity (in years)	
Drought in childhood × Female	3.21
	(12.90)
Flood in childhood × Female	-6.08
	(11.37)
Snow in childhood × Female	24.96
	(15.66)
Low temp. in childhood × Female	-1.71
	(10.65)
Drought in childhood	-7.00*
	(3.93)
Flood in childhood	-11.38**
	(5.76)
Snow in childhood	1.35
	(5.60)
Low temp. in childhood	-2.47
	(5.15)
Female	-19.46**
	(9.02)
Observations	5,102
R-squared	0.17

Only the coefficients of interaction terms are reported. Weather indicators till 40s are controlled for (as in the last column of Table 2). Death decade fixed effects are included. Robust standard errors in parentheses, clustered at the birth decade level. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Survival Analysis (Effects of Weather Shocks)

	(1)	(2)	(3)	(4)	(5)
This is a Gompertz hazard model					
Drought in childhood	1.77**	1.57*	1.55	1.72*	1.82*
	(0.44)	(0.40)	(0.42)	(0.48)	(0.59)
Flood in childhood	1.67	1.69	2.23	2.25	2.43*
	(0.64)	(0.71)	(1.12)	(1.13)	(1.26)
Snow in childhood	0.92	0.76	0.91	1.14	1.04
	(0.29)	(0.32)	(0.39)	(0.58)	(0.55)
Low temp. in childhood	1.05	1.02	1.10	1.03	1.17
	(0.42)	(0.39)	(0.43)	(0.44)	(0.54)
Drought in 1st decade after childhood		1.59	1.35	1.28	1.36
		(0.46)	(0.41)	(0.39)	(0.44)
Flood in 1st decade after childhood		1.93	1.88	2.18	2.10
		(0.80)	(0.83)	(1.07)	(1.08)
Snow in 1st decade after childhood		0.69	0.66	0.86	0.80
		(0.28)	(0.35)	(0.50)	(0.51)
Low temp. in 1st decade after childhood		1.08	1.06	1.03	1.07
		(0.42)	(0.40)	(0.39)	(0.45)
Drought in 2nd decade after childhood			1.60	1.53	1.59
			(0.51)	(0.48)	(0.56)
Flood in 2nd decade after childhood			2.09*	2.19*	2.59*
			(0.89)	(0.98)	(1.37)
Snow in 2nd decade after childhood			0.75	0.96	0.97
			(0.33)	(0.60)	(0.68)
Low temp. in 2nd decade after childhood			1.07	0.95	0.97
			(0.43)	(0.40)	(0.50)
Drought in 3rd decade after childhood				1.53	1.52
				(0.44)	(0.47)
Flood in 3rd decade after childhood				1.86	1.80
				(0.80)	(0.80)
Snow in 3rd decade after childhood				1.42	1.30
				(0.66)	(0.81)
Low temp. in 3rd decade after childhood				0.95	0.85
				(0.41)	(0.43)
Drought in 4th decade after childhood					1.69*
					(0.51)
Flood in 4th decade after childhood					1.24
					(0.54)
Snow in 4th decade after childhood					0.79
					(0.38)
Low temp. in 4th decade after childhood					1.10
					(0.51)
Gamma	1.08***	1.08***	1.08***	1.08***	1.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	5,114	5,114	5,114	5,112	5,102

Death decade and gender fixed effects are included. Robust standard errors in parentheses, clustered at the birth decade level. *** p<0.01, ** p<0.05, * p<0.1.

Appendices

The appendices include a standalone Figure A1 and two supplements. The first supplement (subsection A.1) is related to the second robustness check in Table 4 (see subsection 4.2). The second supplement (subsection A.2) is the third robustness check omitted in the main text. It provides the data source that we use to construct the alternative weather indicators and a discussion of the results.

A.1 The Four Turbulent Periods

Anlushan rebellion. The Anlushan rebellion (755-763) was a deadly rebellion that took place during the Tang Dynasty (618-907). Led by General Anlushan, the revolution spanned the rule of three Tang emperors. Rebel troops captured the eastern capital city of Luoyang in a year, and Anlushan declared himself Emperor of the new Great Yan dynasty. The war had a lasting impact on economic and social systems, and a large proportion of the population died from mass starvation and diseases triggered by the conflict. It is considered to be one of the most devastating conflicts in Chinese history, although the exact death toll is controversial. A comparison of the census reports between the year 755 and the year 764 suggests that up to 36 million died (Fitzgerald, 1985).

Mongol conquest of China. The Mongol conquest of China, a prelude to the creation of the vast Mongol Empire which by the year 1300 had occupied large parts of Eurasia, was also one of the deadliest episodes in Chinese history. Genghis Khan and his descendants launched progressive invasions of China. Starting from his political rise in 1206, Genghis Khan subjugated the Western Xia in 1209 before destroying them in 1227. Genghis Khan (1162-1227) was known for the brutality of his campaigns, and had a fearsome reputation as a genocidal ruler (Man, 2004).

Yuan to Ming dynasty transition. The Ming dynasty (1368-1644) was established following the collapse of the Mongol rule of China. In 1351, when the Yuan dynasty rulers forced 150,000 to 200,000 Chinese laborers to repair the damaged link between the Grand Canal and the Yellow River, the laborers rebelled. This uprising, called the Red Turban Rebellion (1351-1368), initiated the collapse of the Mongol rule over China. This tumultuous period included the Battle of Lake Poyang in 1363, a candidate for the largest naval battle in history, with a reported 850,000 sailors and soldiers involved. The turbulent periods of the Mongol conquest of China and the Yuan to Ming transition left an indelible mark on China's population statistics. The estimated population in the year 1400 was about half the size of the Chinese population in the early years of the 12th century (Broadberry et al., 2018).

Ming to Qing dynasty transition. Prior to the establishment of the Qing dynasty (1644-1912), the last imperial dynasty in China, the Qing conquest of the Ming dynasty (the period 1618-1683, often referred to as the Manchu conquest of China) was a period of extreme political turmoil and a bloody period in Chinese history. The conquest started with a rebellion against Chinese imperial authority in Manchuria (Northeastern China). The Manchu, formerly called the Jurchen people, rose to power under the leadership of a tribal leader named Nurhaci, who commissioned a document titled the Seven Grievances, essentially a declaration of war against the Ming. As the rebellion gained speed and approached Beijing, a series of smaller peasant revolts broke out through the rest of China. Although the Manchu were in control of Beijing by 1644, they did not establish their authority throughout China until 1683. For details of the transition, see Swope (2014).

A.2 Alternative Weather Indicators

We experimented with collecting drought and flood data from Song (1992), a source that differs from Bai and Kung (2011). We keep the droughts and floods as counts (i.e., number of events). In Song (1992), the drought counts are provided as nationwide totals without locations, while the flood counts are provided separately for the Yellow River, the Yangtze river, and the Pearl River. To make the three counts comparable (rivers have different frequencies of floods for natural and institutional reasons) and aggregatable, we first conducted normalization on each of them, and then took the median of the three for each given decade. The regression results are reported in Table A1, which accord with those in Table 3. Drought has a negative and statistically significant impact on longevity. Experiencing one drought reduces longevity by 0.48 years. Flood also has a negative effect on longevity, though the effect is statistically insignificant.

Figure A1: A Sample Page from the BEECH (2002)

姓名	字或號	籍貫	生年	西紀	卒年	西紀	歲數
孔丘	仲尼	魯	周靈王二一庚戌	前五五一	敬王四一壬戌	前四七九	七十三
秦商	不慈	楚	周靈王二五甲寅	五四九			
顏由	季路	魯	周靈王二七丙辰	五四五			
冉耕	伯牛	魯	周景王元丁巳	五四四			
仲由	子路	卞	周景王三己未	五四二	敬王四十辛酉	四〇八	六十三
漆雕開	子若	蔡或曰魯	周景王五辛酉	五四〇			
有若		魯	周景王七癸亥	五三八			
閔損	子騫	魯	周景王九乙丑	五三六			
孔鯉	伯魚	魯	周景王一三己巳	五三二	敬王三七戊午	四八三	五十
冉求	子有	魯	周景王二三己卯	五二二			
商瞿	子木	魯	同				
顏回	子淵	魯	周景王二四庚辰	五二一	敬王三十辛亥	四九〇	三十二

Table A1: Alternative Weather Measures from Various Sources (Companion to Table 3)

	(1)	(2)
Dep. Variable is longevity (in years)		
Drought in childhood	-0.48***	
	(0.18)	
Drought in 1st decade after childhood	-0.12	
	(0.20)	
Drought in 2nd decade after childhood	0.34	
	(0.21)	
Drought in 3rd decade after childhood	0.6	
	(0.18)	
Drought in 4th decade after childhood	0.24	
	(0.17)	
Flood in childhood		-2.09
		(1.39)
Flood in 1st decade after childhood		-1.23
		(1.61)
Flood in 2nd decade after childhood		0.80
		(1.73)
Flood in 3rd decade after childhood		0.05
		(1.66)
Flood in 4th decade after childhood		1.88
		(1.62)
Observations	5,102	5,102
R-squared	0.15	0.16

Death decade and gender fixed effects are included. Robust standard errors in parentheses, clustered at the birth decade level. *** $p<0.01$.