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ABSTRACT

We investigate the long-run effects of cooling on conflict. We construct a geo-referenced and digitized database of conflicts in Europe, North Africa, and the Near East from 1400-1900, which we merge with historical temperature data. We show that cooling is associated with increased conflict. When we allow the effects of cooling over a fifty-year period to depend on the extent of cooling during the preceding period, the effect of cooling on conflict is larger in locations that experienced earlier cooling. We interpret this as evidence that the adverse effects of climate change intensify with its duration.

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1 Introduction

Climate change is one of the most pressing problems faced by countries today. Recent studies provide a large body of important evidence on the adverse effects of weather shocks on economic and political outcomes in the short to medium runs (Burke and Emerick, 2015; Dell et al., 2012; Hornbeck, 2012; Hsiang and Jina, 2014; Miguel et al., 2004). However, much less progress has been made in understanding the effects of longer-run changes in the climate.[1] This is important, because climate change is inherently a long-run phenomenon, and it is unclear whether long-run effects will be more or less detrimental than short-run effects. On the one hand, there may be what the literature commonly refers to as "adaptation". Populations may relocate, or they may adopt new technologies, production processes, crops, or even social or institutional structures that better suit the new environment. Thus, while individuals are unable to adapt to short-run fluctuations in weather, they may be able to adapt to longer-run changes in climate. If this is the case, then long-term effects may be weaker than the short-run effects. On the other hand, there may be "intensification", a term coined by Dell et al. (2014) to refer to the compounding effects of prolonged climate change that occurs over an extended period of time. For example, one year of drought may have few adverse effects by itself, but a year of drought that follows three successive years of drought may have larger adverse effects if, for example, food stores have eroded. Prolonged periods of climate change, over decades or centuries, may also begin to affect more fundamental factors, such as institutions, governance, or even culture. Thus, it is possible that long-term effects may be greater than short-term effects.

The goal of this paper is to provide a better understanding of the long-run effects of climate change, and the potential channels through which these effects operate. To do this, one needs to examine the effects of climate change over long periods of time. Since we do not yet have sufficient time series to examine the effects of modern global warming, we attempt to make progress on this important question by examining periods of dramatic cooling that occurred in Europe, North Africa and the Near East between 1400 and 1900 CE.

Our analysis examines the long-run effects of cooling on conflict and warfare – outcomes fea-

[1] See Dell et al. (2014) for an overview of the climate change literature.

tured prominently in the literature on economic and political development, and for which reliable measures are available to researchers. To measure historical conflict, we construct a new dataset of all wars and each of their battles that were fought between 1400 and 1900 CE in Europe, the Near East, and Northern Africa. The conflict data are constructed using two sources, Brecke (1999, forthcoming) and Clodfelter (2008), which provide information on known wars, including the locations and dates of all battles fought during a war. Over a period of six years, we manually digitized the information and geo-referenced each battle (defined as a conflict event during a war) to construct a dataset that records the date and location of over 2,700 conflicts in Europe, North Africa and the Near East between 1400 and 1900 CE.

We merge the conflict data with historical climate data that were constructed by geologists and climatologists (Mann et al., 2009a). The original data set includes gridded annual average temperature (0.5 degree by 0.5 degree grid-cells) from 500 to 2000, which covers the entire globe.[2] Our baseline sample is at the decade and grid-cell level, where each grid-cell is 400km by 400km. Our grid-cells are large both to match the resolution of the climate data, and also to capture potential spillovers in conflict caused by environmental fluctuations. For example, disruptions to agricultural productivity can lead to migration, which will lead to conflict not just in the original location, but in the destination of the migrants as well.

The length of the 500-year panel allows us to estimate the impacts of climate change over the long term, as well as test for the presence of adaptation and intensification effects. The period we examine includes an era that is commonly referred to as the "Little Ice Age" by climatologists and historians. This was a period of extreme cooling. During this time, glaciers expanded and seas froze as far south as present-day Turkey. Temperature declines were accompanied by increased variability in precipitation. Record levels of precipitation, which were preceded and/or followed by droughts, significantly reduced agricultural productivity, which in turn led to famines and conflicts that took various forms, including rebellions, uprisings, and foreign invasions. During the Little Ice Age, there was temporal and spatial variation in the intensity of cooling.

[2]See Section 4 for a detailed discussion.

Although climate change in our context is one with temperature declines, the findings of our study are relevant for the issue of modern climate change, e.g. global warming. To understand this, it is important to keep several points in mind. First, in general, there is an optimal temperature range for a given form of agricultural production. Thus, our study of historical cooling and studies of modern warming share the common feature that both are examining deviations from the previous level of temperature. Both cases are expected to reduce agricultural productivity, which can lead to conflict. Second, both historical cooling and modern warming are correlated with higher environmental volatility, which can disrupt agricultural production, as well as other economic activities.[3] This fact underlies the climate change literature's use of temperature as a sufficient statistic for capturing environmental changes of the time (Nordhaus, 1993). For these reasons, we expect that both long-run cooling and long-run warming may both be associated with greater conflict. Consistent with this, a number of past studies have documented non-monotonic relationships (resembling U-shaped curves) between conflict and temperature levels.[4]

Our empirical analysis proceeds in several steps. We begin in Section 3 by motivating our baseline specification, where the dependent variable is the change in conflict incidence over a fifty-year period. The main independent variables are the change in average regional temperature over the same period, the change in average regional temperature during the previous period, and the interaction of these two terms. The latter interaction term is the key innovation of our estimation and the focus of our analysis. We interpret it as the net of adaptation and intensification effects since it shows how the effect of cooling in a fifty-year period on the change in conflict during that period depends on cooling in the preceding fifty-year period. A negative interaction effect suggests that adaptation dominates intensification. Cooling that immediately follows a period of previous cooling has smaller marginal effects because society has had time to develop ways of adapting to further change. A positive interaction effect suggests that intensification dominates adaptation. Cooling that immediately follows an earlier period of cooling has larger marginal effects and the current

[3]In Section 4, we document a correlation between cooler temperatures and higher rainfall volatility in the historical data.

[4]For example, Burke et al. (2015) report a U-shaped relationship between conflict incidence and temperature from a panel of East African countries, observed at an annual frequency between 1981 and 2002.

effects of cooling are compounded by the effects of earlier cooling. For example, state capacity might be eroded by long periods of cooling, which might make the region more politically sensitive to further shocks. Alternatively, individuals and societies might constrain and limit belligerence initially on the belief that the adverse climate shocks are transitory. But, with successive climate shocks, they might ratchet up belligerence (or adaptation to the new environmental conditions) once they start to view the new climate conditions as permanent.[5]

The regressions control for time-period (i.e., decade) fixed effects and grid-cell fixed effects. Time period fixed effects control for changes that affect conflict over time that are common across space, e.g., changes in military technologies, changes in agricultural technologies, and broad political changes like the rise of nation states. Grid-cell fixed effects control for time-invariant differences across regions, e.g., geographic characteristics.

The analysis produces several results. First, we find that for a location that experienced a standard deviation more of cooling, but experienced no cooling in the previous period, the change in conflict incidence is approximately 0.03 standard deviations greater. Second, in a location that experienced a standard-deviation of cooling in the previous period, a standard deviation more of cooling in the current period leads to a 0.09 standard deviation increase in conflict change. The first two results together imply that cooling has a three times greater effect on conflict change if the same area experienced cooling during the previous period. While the forces of adaptation may be present, our estimates indicate that they are dominated by the forces of intensification. Third, we find that the coefficient for the direct effect of the previous fifty-years of cooling is close to zero and insignificant. Thus, while cooling during the previous fifty-year period has no direct effect on conflict change during the subsequent fifty-year period, it does have an important indirect effect because it increases the effect that cooling in the subsequent fifty-year period has on conflict change during that same period.

Our baseline specification is intentionally parsimonious, since the introduction of additional covariates can alter the interpretation of the estimates. Nevertheless, to address concerns of omitted

[5] We provide a more detailed discussion and concrete historical examples in Section 2.

variables biases, we show that our results are very similar when we control for additional factors, such as latitude, longitude, elevation, terrain slope, distance to the coast, agricultural suitability, the urban population in 1400, and average temperature in 1401-1450. In our specifications, we interact these time-invariant controls with a full set of time-period fixed effects to allow their influences to vary flexibly over time. We also show that the findings are robust to alternative ways of clustering, to the omission of earlier years when the historical climate data are of lower quality, and to the omission of large wars which may spuriously drive our results. The last robustness check is important for ruling out the concern that our estimates are spuriously driven by a few large wars (with many battles) that happened to have coincided with cooling. In fact, when we divide the sample according to the size of the war, we find that our results are driven by conflicts that are part of medium scale wars. This is reassuring since it is less plausible that cooling was a key determinant of the largest wars, such as the Napoleonic Wars or the wars related to the Reformation. Lastly, we also demonstrate that it is unlikely that the results are due to measurement error in the temperature data.

To shed light on the mechanisms driving the results, we investigate heterogeneous effects. We find that our estimates are strongest in regions that are suitable for the production of agricultural staples, as well as for inland regions that are further from the coast. Both findings are consistent with climate change affecting conflict by reducing agricultural productivity. It had a smaller effect in regions that relied less on agriculture, either due to lower productivity in agriculture or greater access to overseas trade. We also find that the negative effects of cooling were larger in regions that were cooler in 1401-1450. This is consistent with cooling having more adverse effects in regions that were already marginal for agricultural production due to their generally colder climate. In addition, the results show that the effects of cooling were similar for conflicts that were part of civil wars and for conflicts that were part of inter-state wars. However, we find that the effects are concentrated in regions that were politically fractionalized during 1401-1450. This is consistent with politically fractionalized regions being less stable and thus more sensitive to shocks.

Our baseline estimates examine the direct and interaction effects of cooling during two fifty-year periods – i.e., over one hundred years. We also examine longer-term effects of cooling by estimating the contemporaneous and lagged effects of cooling (and their interactions) for five fifty-year periods, i.e., over 250 years. The goal of this somewhat heroic exercise is to take advantage of the long-historical panel data to investigate whether the effect of cooling on conflict change during this fifty-year period is affected by coolingin the previous four 50-year periods. We find that the further back that previous cooling occurred, the less it affects the impacts of recent cooling.

Our paper contributes to two bodies of research. First, we make contributions to the climate change literature. We are the first to provide direct estimates of long-run (i.e., beyond fifty or sixty years) and very long-run effects (i.e., beyond 100 years) on any outcome. Past studies inferred long-run effects indirectly from cross-sectional comparisons (Mendelsohn et al., 1994) or by plugging in short-run estimates into "business-as-usual" models to project long-run effects (Deschenes and Greenstone, 2011). In attempting to estimate causal effects beyond the short-run, we are most closely related to studies of the medium-run effect of climate change in the United States (Burke and Emerick, 2015; Dell et al., 2012), which we discuss in more detail later in the paper, and of the medium-run effects of natural disasters (Hornbeck, 2012; Hsiang and Jina, 2014). Our results are also consistent with the findings of a working paper by Ludlow and Hsiang (2016), which finds no evidence of adaptation to climate change in the historical Irish context.[6]

Our findings provide evidence of long-run intensification effects, and show that the effect of climate change is non-linear with respect to the duration of climate change. To the best of our knowledge, we are the first to estimate long-run interaction effects of this nature and to show empirically the importance of a flexible functional form for capturing such long-run effects. The specification we estimate is discussed, though not estimated, in the review article by Dell et al. (2012).[7] Our

[6]Several recent studies in political science have examined the relationship between climate change and conflict in the historical context. For example, Lee et al. (2013) recently linked historical conflict data provided by Brecke (1999, forthcoming) and climate data from Mann et al. (2009a) to argue that climate change increases conflict. In contrast to our analysis, these findings examine aggregate variation in the time series. By examining variation across both space and time, we are able to provide complimentary evidence for the link between climate change and conflict that is not identified from only time variation. These other studies do not examine interaction effects.

[7]The review points out that the existing literature examines adaptation in the following ways. "First, different geographic areas have different baseline climates. An unusual weather shock in one area is often well within normal experience in another area, where adaptation has had the opportunity to occur. Comparing these areas by interacting weather shocks with the existing distribution of weather events can help assess the magnitude of adaptation. Second,

focus on non-linearity is most closely related to Deschenes and Greenstone (2011) and Schlenker and Roberts (2009), who provide evidence for the non-linear short-run relationship between temperature levels and outcomes in the United States.

Our findings also contribute to a very recent literature that examines the economic effects of climate change during the Little Ice Age. For example, Waldinger (2015) examines the relationship between mean temperatures over 50- and 100-year periods and urbanization from 1500-1750. Dalgaard et al. (2016) examine the relationship between cooling and productivity growth within a panel of 21 countries across centuries from 1000-1800. Our finding that cooling increases conflict complements the findings from these studies, which show that cooling is associated with worse economic outcomes.[8]

Second, our findings also add to the empirical literature on the determinants of conflict. Our investigation of the long-run effects of climate change complements studies of the short-run effects of weather shocks and agricultural price shocks on conflict (e.g., Miguel et al., 2004; Dube and Vargas, 2013). To establish causal identification, studies of the determinants of conflict tend to estimate the impacts of shocks on contemporaneous conflict. For thorough reviews of this literature see Hsiang et al. (2013) and Burke et al. (2015).[9] In studying the long-run determinants of conflict, we are most closely related to studies on the relationship between non-transitory agricultural shocks and conflict in the historical context. For example, in a companion paper, Iyigun et al. (2016) use the same conflict data as this paper to show that the adoption of potatoes in Europe, which increased agricultural productivity, reduced conflict in the 18th and 19th centuries. Similarly, Jia (2014)

one can examine long differences; i.e., instead of looking at annual shocks, one can examine average impacts over longer time horizons, such as decades. Third, one can focus on particular permanent shocks and trace out their impacts over many years. Fourth, combining the previous two methods with short-run panel estimation, one can explicitly compare the same event at different time scales to assess the degree of adaptation. Fifth, one can extend panel models to explicitly examine spillovers of weather shocks". We discuss our empirical specification relative to the existing literature more in Section 3. Our examination of the interaction of climate change in different time periods differs from and complements existing studies.

[8]Our results are also in line with the findings from Anderson et al. (2016), who show that periods of cooling are associated with greater religious violence and persecution against Jewish populations in Europe between 1100 and 1800, and with Oster's (2004) finding of a relationship between cooling and witch killings in Renaissance Europe.

[9]An example of such a study exploiting short-run variation with historical conflict data is Bai and Kung (2011a). Using a long panel which include 2,000 years, they find that rainfall shocks in the previous decade increased nomadic attacks, but shocks during one decade earlier had no effect. Kung and Ma (2014) examine annual data and document a relationship between rainfall-shortages/crop failures and peasant rebellions during the Qing dynasty in China.

finds that the introduction of sweet potatoes acted as an insurance mechanism and reduced peasant rebellions in China during adverse rainfall shocks.

The rest of our paper is organized as follows. Section 2 discusses the historical background. Section 3 motivates the empirical specification, Section 4 describes the data, and Sections 5 and 6 report the empirical results. Section 7 discusses the implications of our results for modern climate change. Section 8 offers concluding thoughts.

2 Background

2.1 Climate Change and Agricultural Production

Prior to the fifteenth century, climate in the northern hemisphere was usually characterized by stable long summers. However, between the early-fifteenth and the mid-nineteenth centuries, the climate became more unpredictable, cooler, and subject to extremes (Lamb, 1995, p. 212). The period of our study (1400-1900 CE) includes the entire era commonly referred to as the "Little Ice Age".[10] This period of cooling reached its peak in the 17th century, which experienced significant cooling. Rivers and seas that previously did not freeze started to freeze over. During the winter of 1620-21, the Bosphorus froze allowing people to walk between Europe and Asia (Parker, 2013, p. 3). During the late 17th century, the ice laid thirty kilometers from shore along parts of the Dutch coast. Many harbors were closed and shipping halted in the North Sea (Fagan, 2000, p. 113).

The exact timing and extent of cooling experienced by different locations in Europe varied and was severe in many locations. For example, data from Zurich from 1560-1599 indicate that temperatures were 1.3 degrees Celsius colder than in 1880–1930 (Lamb, 1995, p. 212). England's average temperature in the late sixteenth and early seventeenth centuries was 0.6-0.8 degrees Celsius colder than in the early 20th century Lamb (1995, p. 212). From 1600-1650, the temperature cooled by up to two degrees celsius in Scotland, leading to a severe reduction in agricultural production. It

[10] There is a debate amongst climatologists about whether or not the Little Ice Age was a large deviation from very long-run historical trends. This is inconsequential for our study.

is believed that 100,000 men, approximately one-fifth of the male population, left Scotland during this period to live abroad (Parker, 2013, p. 100). In Northern Europe, nine out of the fourteen summers between 1666-1679 were abnormally cold (Parker, 2013, p. xxv).

The Eastern Mediterranean is a region that experienced particularly severe changes during the Little Ice Age. Most places in this region suffered drought and plague during the 1640s and 1650s, and again in the 1670s. The winter of 1684 was recorded as being the wettest winter on record during the previous five centuries. The average temperature during the winters of the late 1680s are estimated to have been a remarkable 3 degrees Celsius cooler than today (Parker, 2013, pp. 209–210).

Like modern global warming, during the "Little Ice Age", periods of climate change were characterized by high variability in precipitation, particularly in the summer (Lamb, 1995, p. 213), which in turn reduced agricultural output (Parker, 2013, ch. 3). Cycles of excessive cold and unusual rainfall often lasted for a decade or longer (Fagan, 2000, p. 48). Cold spells during germination, droughts during the early growing season, and major storms at harvest were particularly disastrous for crops. As an example, in Baden of Southwest Germany, the frequency of good wine years from 1550-1620 was less than half the frequency of 1480-1550 Lamb (1995, p. 213). Climate also affected crops indirectly. Excessive rain encouraged rodents, while droughts encouraged locusts (Parker, 2013, p. 18). Severe cooling made previously productive lands located at higher altitudes and latitudes unusable, and the expansion of glaciers made previously habitable lands uninhabitable. As well, successive years of flooding and excessive rain washed away the nutrients in the soil that took decades to replenish. For example, it is estimated that between 1628 and 1630, Chamonix lost a third of its land through avalanches, snow, glaciers, and flooding (Fagan, 2000, p. 124).

The reduced availability of food caused population declines through increased mortality, reduced fertility, and out-migration. For example, during the mid-17th century, the population in Ireland fell by at least one-fifth, the rural population in Germany declined by thirty to forty percent, and in Poland and Russia populations fell by one-third (Parker, 2013, p. 25). Seventeenth-century

Finland saw eleven complete crop failures (Parker, 2013, p. 18). By the end of the century, Finland had lost as much as a third of its population from famine and disease (Fagan, 2000, p. 132). Possibly the hardest hit region during this time was the Balkans and Anatolia, which according to estimates, lost about half of its population during the 17th century. By the mid-17th century, rural populations in some regions in Anatolia fell by as much as 80 percent, while 30-40 percent of rural villages were abandoned and left empty. Estimates from Boeotia, Greece indicate that by 1688, the population was half of what it had been just a century earlier (White, 2011, pp. 204-211). The lack of nutrition during these periods of cooling are also apparent in skeletal remains that show the stunting of French soldiers born during these periods and in populations from Holland (Parker, 2013, p. 22).

The drastic reduction in agricultural productivity typically caused surges in food prices. For example, severe cooling in 17th century Scandinavia led to crop failures, which caused "bread prices to climb far beyond the reach of families already weakened by two decades of [bad harvests and] war" (Parker, 2013, p. 230). In France, consecutive years of bad weather during the same period drove bread prices to the highest levels in over a century. Similar relationships between crop failure and high food prices were also seen in other locations, such as Britain and Switzerland during the 1730s (Fagan, 2000, p. 139). A recent study by Waldinger (2015) provides quantitative evidence of the relationship between cold temperatures and higher wheat prices across ten European cities during this period. According to her estimates, a one degree Celsius decline in temperature caused an increase in the average wheat prices of 11 percent. These effects are important, especially given that in Europe cereals provided approximately three-quarters of total caloric intake (Parker, 2013, p. 19).

This period of cooling not only affected agriculture, but for some locations, the fishing industry as well. During the coldest period of the seventeenth century, sea temperatures along the Norwegian coast fell by two degrees Celsius within a 30-year period. During this time, the Faroe cod fisheries stopped producing as the sea surface temperature became five degrees colder than today. The lack of cod was due to the fact that the fish cannot survive in water that is colder than 2 degrees Celsius

(Lamb, 1995, pp. 217–219). These effects were widespread, with production declining significantly as far south as the Shetland Islands (Fagan, 2000, pp. 70, 116).

An aspect of this period of cooling, which is crucial for our analysis which exploits variations across both space and time, is that climate change was not uniform across regions or over time. As Fagan explains: "Climate change varied not only from year to year but from place to place. The coldest decades in northern [western] Europe did not necessarily coincide with those in say Russia" (Fagan, 2000, p. 50). In fact, the Russian Empire absorbed a significant number of emigres from devastated regions such as France and Germany. This variation was due, in part, to differences in geography, with coastal and high altitude areas tending to be more affected due to the freezing of coastlines and the movement of glaciers.

2.2 Climate and Conflict

Several historians and political scientists have noted that upticks in historical conflict were associated with climate change (e.g., Lamb, 1995). A number of scholars have also documented links between aggregate climatic fluctuations and conflict historically, including in China (Zhang et al., 2006, 2007; Bai and Kung, 2011b; Jia, 2014), Africa (Fenske and Kala, 2015), and Europe (Zhang et al., 2007; Tol and Wagner, 2010; Lee et al., 2013). Other studies have examined more specific forms of violence and conflict. For example, Anderson et al. (2016) look across 936 European cities between 1100 and 1800 and document that colder temperatures were associated with more violence against Jewish populations. Oster (2004) shows that in the aggregate between 1520 and 1770, cooling is associated with more violence and accusations of witchcraft.

There is ample historical evidence suggesting that the reduction in agricultural productivity that resulted from cooling led to different types of conflict. There are examples of peasant rebellions in times of famine (Parker, 2013, chpt. 3). Historians have also linked foreign invasions to climate change – particularly to cooling. There are many potential reasons behind this relationship. This could have been due to a reduction in the cost of invasion because natural barriers such as rivers or seas froze over and allowed for easier troop movements. Or because reduced agricultural production increased demand for other sources of revenue, which incentivized governments to invade relatively fertile neighbors. At the same time, belligerent neighbors sometimes viewed the weakening of state capacity caused by climate change as a good opportunity for invasion. For example, from 1686-1687, the Ottoman Empire experienced its second severe cold spell of the century – this was the second time that the Golden Horn froze over – and for several years, it experienced winters with little precipitation and summers with record-high levels of precipitation. The impoverished government did not pay its army, which mutinied and forced Mehmet IV to abdicate, resulting in the fifth forced removal of an Ottoman Sultan in sixty years. During this time, the Hapsburgs and Venetians attacked. In 1699, after the Golden Horn froze again, the Ottomans signed the Treaty of Karlowitz where it ceded most of modern Hungary and Greece (Parker, 2013, p. 209). During periods of climate change, conflicts of different forms often occurred simultaneously. For example, in the early 1600s in Russia, twenty years of famines, rebellions, and civil wars, as well as invasions by both Sweden and Poland had reduced the size of the Russian population by approximately one-quarter (Parker, 2013, p. 152).

The impoverished agricultural sector made it easy for governments to recruit soldiers. After the Great Winter of 1708-9, a French general said "we could only find so many recruits because of the misery of the provinces…The misfortune of the masses was the salvation of the kingdom" (Parker, 2013, p. 101). Thus, another reason why climate change may have increased conflict was by reducing the cost of arming.[11]

2.3 Adaptation and Intensification

In many of the examples that we have provided, the effects of climate change on conflict intensified as periods of climate change prolonged. More generally, historical accounts suggest that continued climate change weakened state capacity, which in turn reduced internal political stability and made states vulnerable to external invasion as well as internal strife. A striking example of this is the

[11]This is consistent with the the contemporary evidence of the relationship between the reduced opportunity costs of conflict in the face of adverse agricultural shocks. See fore example Miguel et al. (2004).

Ottoman Empire. Parts of the Ottoman Empire experienced severe cooling and suffered repeated agricultural productivity shocks during the late 16th and the early 17th centuries (White, 2011). In several regions of Anatolia, the number of rural taxpayers fell by three-quarters between 1576 and 1642, and almost half of all villages disappeared (Parker, 2013, p. 188).

At the same time, historical accounts also give examples to suggest that afflicted populations were able to adapt with time. There are numerous accounts of migration and the relocation of economic activity. Production of certain types of crops permanently ceased in some regions. In Britain, wine production was significantly reduced by exceptionally harsh winters during the 1430s, and in 1469 wine production stopped altogether. Historians also argue that farmers sometimes adapted to their new environments by experimenting with new agricultural technologies, which improved productivity. For example, Flemish and Dutch farmers used windmills to drain the land of excess precipitation and began to experiment with lay farming and crop rotation. During the 1600s, Dutch engineers developed better methods for reclaiming land and protecting against floods (Fagan, 2000, p. 107). To cope with colder winters, farmers from Northern Europe introduced turnips and potatoes as field crops in the late-1600s and early-1700s (Fagan, 2000, pp. 108–109).[12] Another example is the experience of Norway, where the traditional industry of fishing suffered severely from the cold temperatures of the 17th century. By the beginning of the 18th century, many coastal villages had been abandoned – and instead – the population engaged in logging, the export of timber, and ship building. Norway developed a large merchant fleet based on the timber trade, which transformed the economy of its southern regions (Fagan, 2000, p. 116).

3 Empirical Framework

The aim of our analysis is to understand the effects of prolonged climate change on conflict. Our empirical specification is guided by the recent review article by Dell et al. (2014). Studies of cli-

[12]The effects of new crops are ambiguous ex ante since sometimes, the lack of knowledge caused cultivation to interact poorly with environmental change. For example, the production decline in Ireland in the 18th century was partly caused by the potato's vulnerability to precipitation (long droughts followed by excessive rains) (Fagan, 2000, Chpt. 11).

mate change typically have in mind an underlying model that assumes that the relationship between temperature and the outcome of interest is locally linear and that there is an optimal temperature. Deviations from the optimal level in either direction has detrimental impacts, reducing productivity, increasing conflict, etc. The setting we study is one in which already-cold environments became colder. This differs from studies of modern climate change that tend to focus on already-warm environments becoming warmer.

Studies of climate change tend to focus on the short-run effects of temperature (or rainfall) levels on outcomes such as conflict, agricultural productivity, or income (e.g., Dell et al., 2012; Deschenes and Greenstone, 2011; Miguel et al., 2004). Using panel data, such studies estimate equations that take the following form:

$$y_{i,t} = -\alpha T_{i,t} + \rho_i + \varsigma_t + \varepsilon_{i,t}, \tag{1}$$

where an outcome (measured in levels) in region i and time period t, $y_{i,t}$, is a function of the level of the climate variable, typically temperature or rainfall, $T_{i,t}$, as well as region fixed effects, ρ_i, and time fixed effects, ς_t. For the purpose of simplifying the discussion, we will simply refer to T as a measure of temperature. Variations in temperature, $T_{i,t}$, is assumed to be exogenously given. Region fixed effects control for time-invariant differences across regions that would affect conflict levels, such as terrain ruggedness or agricultural suitability. Time fixed effects control for any changes in the determinants of conflict that are common across space, such as innovations in military technology.

In our setting, the cross-sectional unit i is a grid-cell, and the time period is a decade, denoted d. The outcome of interest, $y_{i,d}$, is the incidence of violent conflicts in grid cell i during the decade d.

To estimate effects of continued climate change beyond the short run using year-to-year variation, existing studies have adopted two different strategies. The first is to plug the short-run estimates into a model that assumes that the long-run "production function" is the same (or similar) to the short-run one. A well-known recent example of this is Deschenes and Greenstone (2011), which finds that in the short-run, very high and very low temperatures are associated with higher mortality rates. Applying these estimates to a "business-as-usual" model predicts that climate change will increase mortality by three percent in the next century. Interestingly, they document a similarly non-linear relationship between temperature and energy consumption, which they interpret as evidence that heating and cooling are used to mitigate the negative effects of extreme temperatures, i.e., technology can adapt to mitigate the effects of climate change.

A second approach examines changes in temperature over longer time intervals (i.e., long-differences) to estimate the medium- or longer-run effects of climate change (e.g., Dell et al., 2012; Burke and Emerick, 2015). In our setting, we follow a similar logic. We use a decade as the unit of observation, which we index by d. For each decade, we then take a fifty-year difference, i.e., the average temperature value for a decade minus the value five decades earlier. We denote this five-decade difference by Δ. Thus, our regression equation is:

$$\Delta y_{i,d-5} = y_{i,d} - y_{i,d-5} = -\alpha(T_{i,d} - T_{i,d-5}) + (\varsigma_d - \varsigma_{d-5}) + (\varepsilon_d - \varepsilon_{d-5}) = \alpha \Delta C_{i,d-5} + \delta_d + \epsilon_{i,d}, \quad (2)$$

where $\Delta C_{i,d-5} = -(T_{i,d} - T_{i,d-5})$ is the decrease in average temperature (i.e., extent of cooling) from decade $d-5$ to d. Thus, $\Delta C_{i,d-5}$ is the negative of an increase in temperature. Therefore, it is positive in sign if there is cooling. Lastly, $\epsilon_d \equiv \varepsilon_d - \varepsilon_{d-5}$ and $\delta_d \equiv \varsigma_d - \varsigma_{d-5}$. In our analysis, we measure conflict, $y_{i,d}$, using an indicator variable that equals one if there was conflict in grid-cell i during any year of decade d. By taking first-differences, we net out any time-invariant differences in a location's propensity to engage in conflict. This addresses, for instance, the possibility that there may be time-invariant differences, such as income or agricultural production, that may themselves be correlated with conflict. The specification also includes time-period fixed effects, δ_d. These capture differences over time that are common to all grid cells.

An important point about equation (2) is that it does not include grid-cell fixed effects, since they are differenced away when we move from equation (1) to (2). A concern with not controlling for location fixed effects is that cooling may have occurred in regions that experienced changes in other factors that could have influenced conflict change. One possibility is to add location fixed effects, which will capture differences in the average changes in conflict over the fifty-year intervals across different locations. To be as conservative as possible, our final specification also includes location (i.e., grid-cell) fixed effects, ρ_i:

$$\Delta y_{i,d-5} = \alpha \Delta C_{i,d-5} + \delta_d + \rho_i + \epsilon_{i,d}. \tag{3}$$

Equation (3) effectively examines the relationship between cooling and conflict change during overlapping windows that are five decades in length.[13] This strategy has many benefits. First, because the unit of observation is a decade (and the measures used are averages during that decade), we can make use of fine-scale variations in conflict and temperature. We are unable to examine the data at a finer level – e.g., annually – since the reconstructed climate data are not reliable at frequencies finer than a decade (Mann et al., 2009b,a). Second, by differencing over fifty-year periods, we can examine how longer-run changes in cooling affect conflict. Since our analysis examines all decades (and not, for example, every fifth decade) we maximize the information that our estimates exploit. Because our differences do contain overlapping decades, observations will not be independent. To address this, we cluster all standard errors at the grid-cell level. Third, since equation (3) includes time-period fixed effects, our estimates of interest are determined by the effects of climate change that deviate from changes that are common to all locations in our sample. Thus, our estimates are not influenced by aggregate trends that are common to all locations. Similarly, equation (3) also includes grid-cell fixed effects, which capture differences in the average change in conflict incidence across locations.

Given our interest in estimating the presence of intensification and adaptation effects, we augment equation (3) and allow for the possibility that cooling in the previous fifty-year period may affect the change in conflict during the current fifty-year period. In addition, we allow cooling in the previous fifty-year period to affect how cooling in the current fifty-year period affects conflict

[13] We discuss alternative interval lengths in more detail in Section 4.

change during the same period. Thus, our regression equation takes the following form:

$$\Delta y_{i,d-5} = \alpha_1 \Delta C_{i,d-5} + \alpha_2 \Delta C_{i,d-10} + \beta(\Delta C_{i,d-5} \times \Delta C_{i,d-10}) + \delta_d + \rho_i + \varepsilon_{i,d}, \tag{4}$$

where everything is defined as in equation (3), including Δ, which continues to denote a difference over fifty years. The new expression, $\Delta C_{i,d-10}$, denotes the difference in cooling between five decades prior and ten decades prior to the current decade: $\Delta C_{i,d-10} = -(T_{i,d-5} - T_{i,d-10})$. The change in conflict over a fifty-year period in grid-cell i, $\Delta y_{i,d-5}$, is now a function of: cooling over the same fifty-year time period in grid-cell i, $\Delta C_{i,d-5}$; cooling during the previous fifty-year period in grid-cell i, $\Delta C_{i,d-10}$; and the interaction of these two periods of cooling, $\Delta C_{i,d-5} \times \Delta C_{i,d-10}$.

It is easy to see that equation (3) is a special case of equation (4), where $\alpha_2 = 0$ and $\beta = 0$. The more-flexible equation (4) allows the effect of cooling in the previous fifty-year period to directly affect the change in conflict in the subsequent fifty-year period, i.e., $\alpha_2 \neq 0$. In addition, equation (4) allows the extent of cooling in the previous period to alter the contemporaneous effect of cooling on conflict change. The marginal effect of cooling during a fifty-year period on conflict change in that same fifty-year period, where each period cools by 1 degree Celsius, is given by $\alpha_1 + \beta$. The estimate of β provides evidence for the presence of adaptation and intensification effects.

It is important to recognize that we are not able to separately identify the magnitude of adaptation effects and intensification effects, but only the net effect of both. If $\beta < 0$, then this provides evidence for the presence of adaptation effects, and to the extent that intensification effects also exist, suggests that adaptation effects dominate the intensification effects. Analogously, if $\beta > 0$, then this implies that intensification effects exist, and to the extent that adaptation effects are also present, they are dominated by intensification effects.

There are many potential omitted variables that can confound the interpretation of the estimates. For example, the historical evidence discussed earlier suggests that cooling was more pronounced in coastal areas, which may have experienced changes in other factors that could have influenced conflict. Thus, after we present our baseline results, we check the robustness of our estimates to also account for these other factors. As we will show, the baseline estimates are, if anything, conservative relative to the estimates that we obtain when we include additional controls.

4 Data

4.1 Conflict

The primary source used to construct our conflict dataset is Michael Clodfelter's (2008) *Warfare and Armed Conflicts*, which is a statistical encyclopedia of global conflicts between 1494 and 2007 CE. This is the most comprehensive source of data available on conflicts over a long time horizon. We extend the Clodfelter data back to 1400 using a second source, Peter Brecke's *Conflict Catalogue*, which contains an annual record of all violent conflicts with 32 or more combat deaths, starting in 1400 CE.[14] Although both sources have widely drawn upon various scholars in different ways (Wimmer and Min, 2006; Zhang et al., 2007; Iyigun, 2008; Dencecco, 2009; Dencecco and Prado, 2012; Lee et al., 2013; Besley and Reynal-Querol, 2014; Iyigun et al., 2016), the data had not yet been digitized for the full time period available and for all of greater Europe. In addition, the locations of battles had not been geocoded. Although the locations of the battles were reported in Clodfelter, they were not reported explicitly in Brecke. For the conflicts that were in Brecke but not Clodfelter, we obtained the locations from other sources such as Shaw (1976), Levy (1983) and Findlay and O'Rourke (2007).[15] We chose to use two sources, rather than one, to maximize coverage and to allow each to cross-check the other.[16] While we used the two most widely consulted sources, we do recognize that a number of other sources also exist. Ultimately, due to resource constraints,

[14]For each conflict recorded in the catalog, the primary information covers (*i*) the number and identities of the parties involved in the conflict; (*ii*) the common name for the confrontation, if it exists; and (*iii*) the date(s) of the conflict. On the basis of these data, there also exists derivative information on the duration of conflicts and the number of fatalities, although these are only available for less than a third of the sample.

[15]For the Brecke data, where we had to consult additional sources, we collected up to four different locations for the primary battles fought in each war.

[16]According to our procedure, prior to 1494, we rely solely on Brecke. Of the two sources, Clodfelter, though its coverage does not extend as far back in time, is more comprehensive since it reports information on battles and not just wars. Thus, we use this as our primary source and use Brecke to extend the dataset back to 1400 and to cross-check Clodfelter. Our results are robust to using only the Clodfelter data. These are available upon request.

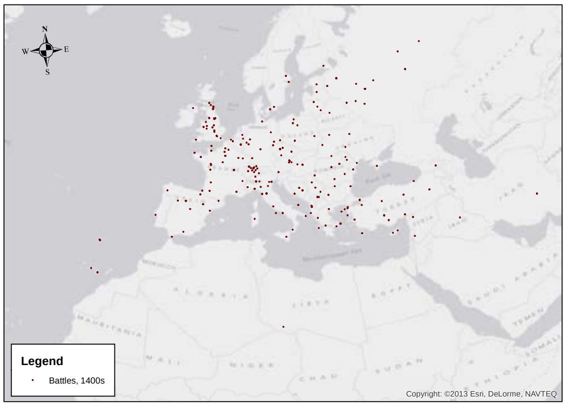
and the time necessary to cross-check multiple data sources against one another, we chose to rely on only two sources.

Our constructed conflict dataset is a panel of all conflicts fought on land by location and year. In total, there are 2,787 battles, defined as a conflict location in a calendar year. While our underlying data are at the conflict level, it is interesting to note that conflicts belong to larger wars. The 2,787 battles in our sample belong to 912 wars. We are able to code several characteristics at the war level. For example, we can compute the size of the war in terms of the number of conflicts (battles within a location and calendar year). On average, there are two conflicts per war. But this masks significant variation, from one conflict (which is common) to 74 conflicts (during the peninsular Napoleonic War, 1807-1814). Around 20% of battles belong to single-conflict wars. We also know whether a war was an inter-state conflict (involving actors from multiple states) or an intra-state one (involving actors from within a state). Later, we will use this information to divide the conflict data.

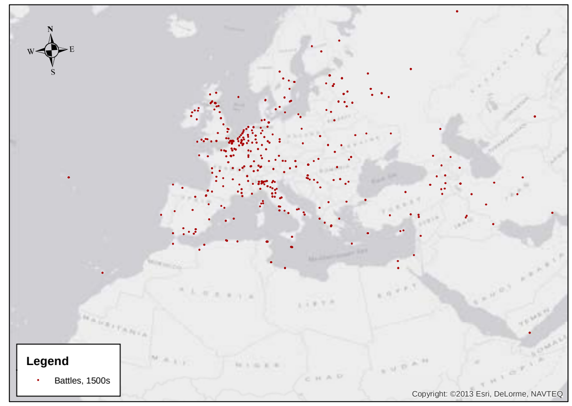
Using this information, we construct a balanced panel of the number of conflicts in a 400km by 400km grid-cell and in a decade from 1401–1900. The size of our grid-cells is determined by the variation in the historical climate data, which we discuss in the next section. The grid-cells are fairly large. For example, modern day France is the same size as approximately four grid-cells. This is important since it means that grid-cells likely capture localized spillover effects; for example, disruptions to local agricultural productivity can lead to migration, which can lead to conflict not just in the original location, but also neighboring destinations of the migrants. Smaller grid-cells are less likely to capture these spillover effects than our 400km by 400km grid-cell.

Figure 1 shows a map of the locations of the conflicts in our database for each century of our sample. It shows that, over time, conflicts moved from being mostly in the Northwest of our sample to the Southeast. Motivated by this, in our robustness analysis, we are careful to check that our results are robust to controlling for latitude interacted with time effects.

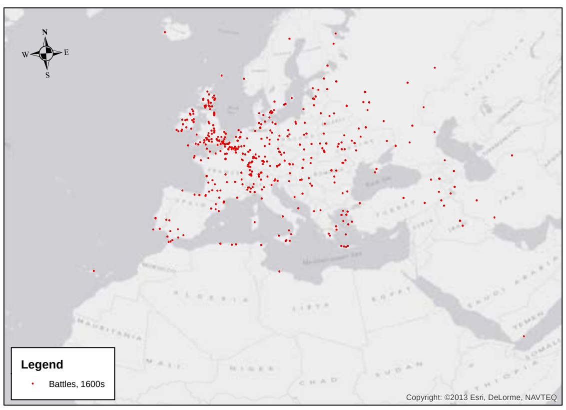
Following existing empirical studies on conflict, such as Miguel et al. (2004), our main outcome variable is the incidence of conflict, measured with an indicator variable that equals one if at least one conflict occurred in a grid-cell at any time during the decade. A benefit of this measure is



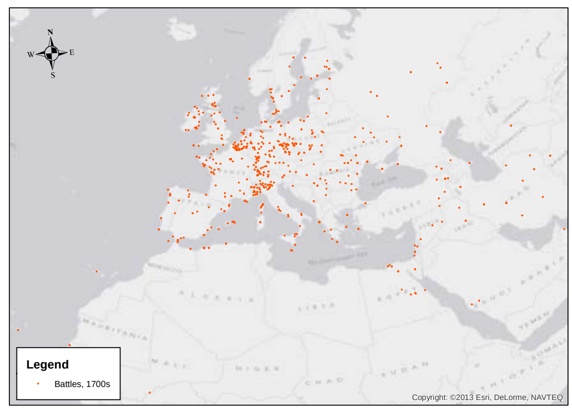
(a) 1401-1500



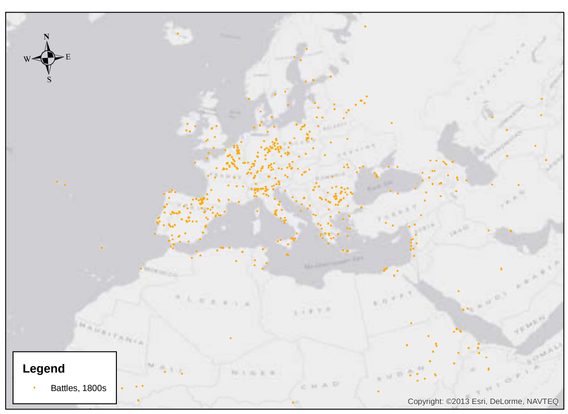
(b) 1501-1600



(c) 1601-1700



(d) 1701-1800



(e) 1801-1900

Figure 1: Locations of conflicts during each century of our sample.

that our estimates are easily comparable to pre-existing studies that examine the short-run effects of weather on conflict. Another benefit is that it helps to mitigate concerns of measurement error relative to, for example, a measure of the number of battles, which is more likely to be measured imprecisely.

4.2 Climate

To measure cooling, we use temperature data constructed by Mann et al. (2009a). The authors use a climate field reconstruction approach to reconstruct global patterns of surface temperature for a long historical period. The construction uses proxy data with global coverage that comprise 1,036 tree ring series, 32 ice core series, 15 marine coral series, 19 documentary series, 14 speleothem series, 19 lacustrine sediment series, and 3 marine sediment series. The data have global coverage and report the average annual temperature for five degree latitude by five degree longitude grids, and are available for each year from 500 to 1959 CE.[17] The data are most accurate for the post-medieval period in the Northern Hemisphere, where our study takes place, because of the larger number of climate proxies from this context.

The data accurately estimate decadal temperature averages but not for finer time periods. Similarly, they are accurate as averages over space, but not for finer geographic locations. The resolution and quality of the data are the key determinants of our analysis being at the decade and 400km by 400km grid-cell level.

Historical temperature data are reported as deviations, measured in degrees Celsius, from the 1961–1990 mean temperature. To be succinct, we will refer to these temperature deviations as temperature in the paper. Figure 2a plots the average temperature for each decade. On average, the decade-average means are below zero, which means that the period we study is on average cooler than 1961–1990. Consistent with historical accounts, the data show three periods of dramatic cooling. The first begins during the middle of the 15th century and lasts until the end of the same

[17]One degree latitude is approximately 111km, and one degree longitude ranges from approximately 111km (at the equator) to 85 kilometers at 40 degrees North to 20 kilometers at 80 degrees North.

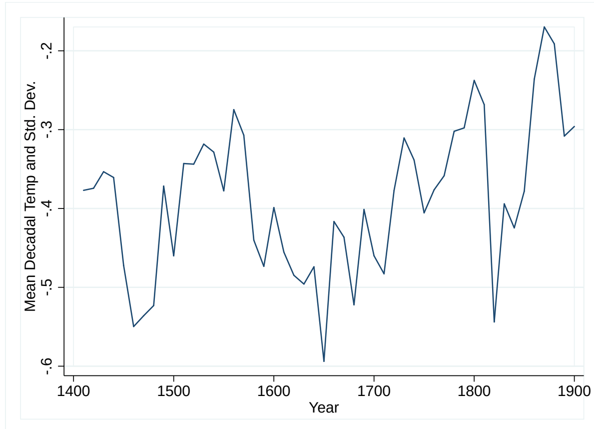
century. The second begins at approximately the beginning of the 17th century and lasts for one hundred years. The third is of shorter duration and occurs towards the beginning of the 19th century and lasts for three decades.

Figure 2b shows the decade-level average temperatures along with the standard deviations of temperatures within a decade. It shows that there is significant spatial variation in temperature for any given decade. To better illustrate the longer-run trends, Figure 2c plots the fifty-year moving averages of temperature. The pattern corresponds to historical accounts that show severe cooling during the late 15th century, the mid-17th century and the early 19th century. The figure shows that the long-run trend is flat and that mean temperatures tend to cycle between cooling and warming. The average change in temperature over the time period of analysis is around zero, which means that over the 500-year sample period, the extent of cooling roughly equals the extent of warming on average.[18]

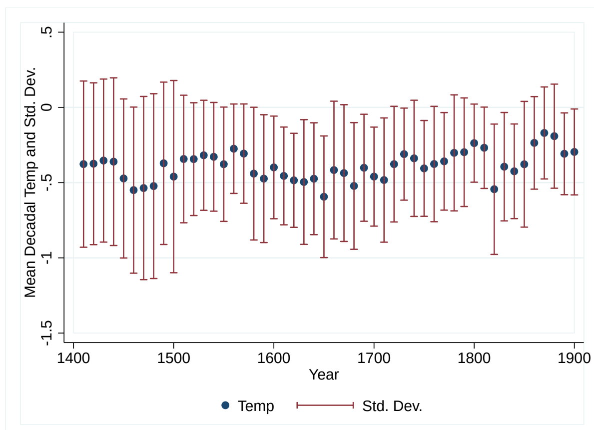
To get a better understanding of the variation across space and time of the extent and duration of cooling, for each grid-cell we calculate the number of decades when there was cooling (i.e., when the average temperature in this decade is lower than the average temperature in the previous decade). The data show both that cooling often persisted over long periods of time and that the duration (persistence) varied across grid cells. For example, over a course of 250 years (i.e., 25 decades), the average grid cell experienced almost ten decades of cooling. However, the cell that experienced the least cooling only experienced it for two decades, whereas the grid cell that experienced the most cooling had cooling in 18 out of 25 decades.

As an alternative strategy to analyze the spatial variation in cooling, we map the magnitude of cooling, measured in degrees Celsius, during three fifty-year intervals, 1451-1500, 1651-1700 and 1851-1900. This is shown in Figure 3. For each period, we divide the grids into ten equal-sized groups according to the extent of cooling. Dark orange marks the grids that experienced the least cooling this period. Dark blue marks the grids that experienced the most cooling. Several facts emerge from the maps. First, there is significant spatial variation in each period. Second, cooling

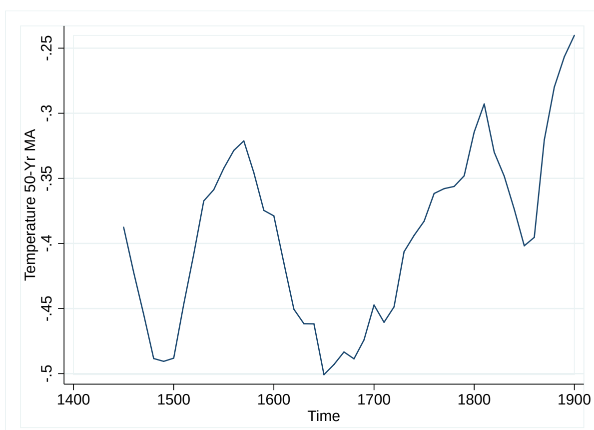
[18]Specifically, $\overline{\Delta C_{i,d-5}} = -.0084$ ($std.dev.$ 0.033). In our sample, mean conflict incidence change is also zero: $\overline{\Delta y_{i,d-5}} = -.0004$ ($std.dev.$ 0.014).



(a) Decadal Means – Main Measure



(b) Decadal Means and Standard Deviations



(c) fifty-Year Moving Average

Figure 2: Temperature over Time

Notes: The historical temperature data are constructed by Mann et al. (2009a). They are reported as deviations from the 1961-1990 mean temperature in degreesCelsius.

is not concentrated along latitude or longitude, or in a given region. Third, there is significant variation across our 400km by 400km grid-cells, suggesting that the use of larger grid-cells may result in the loss of important variation.

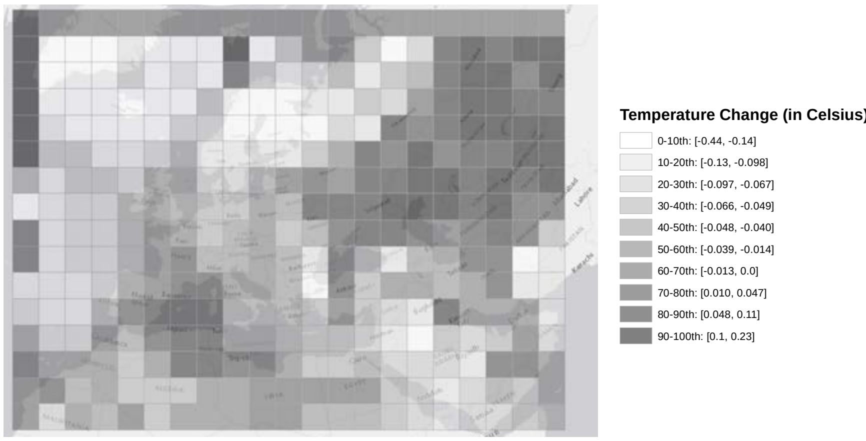
Finally, there is significant variation across time in the spatial distribution of cooling. For example, Figure 3a shows that, during the second half of the 15th century, there was significant cooling along the Atlantic coast and in the eastern Mediterranean. Figure 3b shows that during the late 17th century, the most severe cooling was felt in eastern Europe, in present-day Ukraine, and western Russia. Figure 3c shows that, during the late 19th century, cooling lessened in eastern Europe, but was greater in northern Europe.

Within our sample period, the main concern is that the earlier centuries in our sample have lower quality data, and that the estimates from some grid-cells are based purely on extrapolation. After we present the baseline results, we will check that our main findings are robust to the exclusion of data from earlier periods, and to the exclusion of grid-cells for which underlying climate proxy measures do not exist.

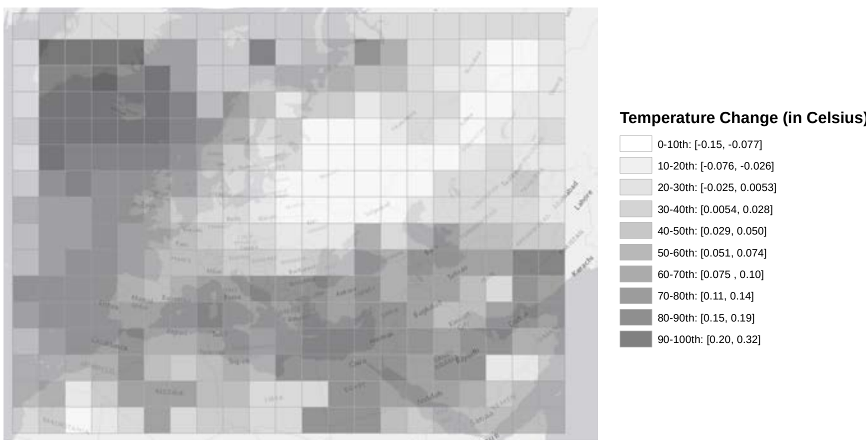
There exists an alternative source of historical temperatures that has been constructed by Luterbacher et al. (2004). These have been used in studies such as Durante (2010) and Waldinger (2015). They are reported every three months (i.e., at the season-year level) and at a 0.5 degree resolution. Thus, both spatially and temporally, these data are more disaggregated than the data from Mann et al. (2009a). However, the Luterbacher data only extend back to 1500 and have much more limited geographic coverage (they do not include North Africa, Eastern Europe, or the Near East). We choose to use Mann et al. (2009a) as our baseline climate measures since, for the purpose of estimating the macro-level long-run effects of climate change, the benefits of more expansive geographical and temporal coverage outweigh the disadvantages of less fine-grained data.

4.2.1 Temperature as a Sufficient Statistic for Climate Change

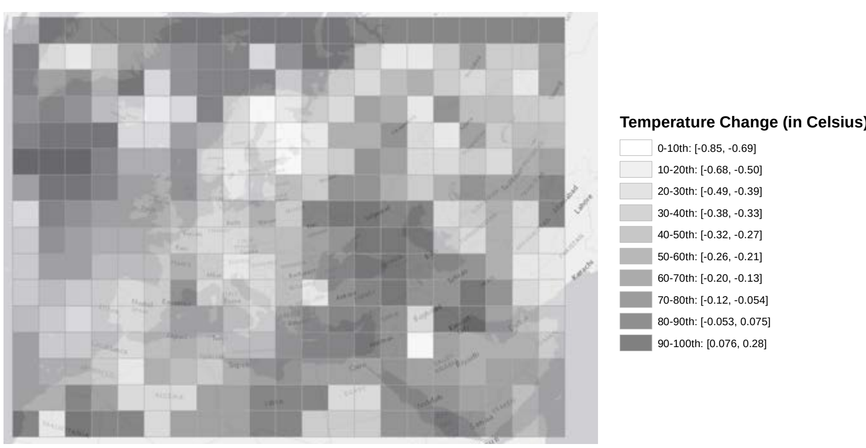
Our measures of climate change are based on temperature, and we interpret temperature as a sufficient statistic for climatic events that reduce agricultural productivity. This is consistent with



(a) 1450-1500



(b) 1650-1700



(c) 1850-1900

Figure 3: Relative cooling across grid-cells for select fifty-year periods. Lighter shades indicate more cooling (more negative changes in temperature).

historical accounts which suggest that the Little Ice Age was associated with "a greater frequency of severe weather events – such as flash floods, freak storms, prolonged droughts and abnormal (as well as abnormally long) cold spells." (Parker, 2013, p. 27). It is also consistent with modern research on climate change. As Nordhaus explains: "In thinking about the impact of climate change, one must recognize that the variable focused on in most analyses – global averaged surface temperature – has little salience for impacts. Rather, variables that accompany or are the result of temperature changes – precipitation, water levels, extremes of droughts or freezes, and thresholds like the freezing point. . . will drive the socioeconomic impacts. Mean temperature is chosen because it is a useful index of climate change that is highly correlated with or determines the more important variables" (Nordhaus, 1993, pp. 14–15).

To verify the historical relationship between temperature and rainfall, we combined the temperature data from Mann et al. (2009a) with precipitation data from Pauling et al. (2006), which is available for the entire time period of our study, but has more limited geographic coverage (essentially Western and Central Europe only). Examining variation in temperature and precipitation across decades and grid-cells, we find that the bivariate relationship between the two is strong and positive. According to the magnitude of the relationship, a one-standard-deviation increase in cooling is associated with an increase in average precipitation of 0.47 standard deviations. The relationship also remains if we add grid-cell or time-period fixed effects. We find that a one-standard-deviation increase in cooling is associated with a 0.67 standard-deviation increase in precipitation if we condition on grid-cell fixed effects; a 0.47 standard-deviation increase in precipitation if we condition on decade fixed effects; and a 0.53 standard-deviation increase in precipitation if we condition on both. Examining relationships with rainfall volatility (the standard deviation of rainfall across years within a decade), we find that a one-standard-deviation increase in cooling is associated with the following increases in volatility, measured in standard deviations: 0.34 (raw data), 0.17 (grid-cell fixed effects), 0.36 (decade fixed effects) and 0.05 (both fixed effects). Thus, consistent with historical accounts (e.g., Fagan, 2000), the data indicate that cooling is associated with higher average precipitation and greater volatility.

5 The Long-Run Effects of Cooling on Conflict

5.1 The "Short-Run" Effects of Temperature on Conflict

Before turning to the primary focus of our paper, which is testing for the presence of adaptation and intensification effects, we first examine the effect of cooling on changes in the incidence of conflict. We begin by first estimating equation (1), which reports the relationship between the levels of temperature and conflict. Given the large body of evidence that colder weather during our context caused instability and conflict, these estimates serve as a check on the validity of the data and their construction. In estimating equation (1), we take a decade as the unit of observation, with temperature measured as the average during the decade, and conflict incidence equals one if there was at least one conflict in that location at any point during that decade. The estimates are reported in column (1) of Table 1. The estimated coefficient for temperature is negative and highly significant, showing that during this period, more cooling was associated with a higher likelihood of conflict. According to the magnitude of the estimates, decreasing temperature by one-standard-deviation (0.404 degrees Celsius) increases the probability of conflict by $0.404 \times 0.0299 = 0.012$ or 1.2 percentage-points. This is a non-trivial effect, since the average incidence of conflict is 8.8 percentage-points (and the standard deviation is 28 percentage-points). These estimates are consistent with the historical accounts discussed in Section 2, as well as previous findings based on aggregate time series data (e.g., Zhang et al., 2007; Lee et al., 2013).

5.2 Baseline Results

The primary interest of our study is in better understanding how the impact of cooling on conflict change depends on a location's earlier cooling. We begin by first estimating equation (3), which follows studies such as Dell et al. (2012) and Burke and Emerick (2015) that estimate the medium-run effects of climate change. The estimates, which we report in column (2) of Table 1, show a strong positive relationship between the extent of cooling during a fifty-year period and the change in conflict incidence during the same period. According to the magnitude of the estimates, a one-

Table 1: The Effect of Cooling on Conflict: Baseline Estimates and Checks of Sensitivity to Functional Form

	Dependent Variable:									
	Conflict Incidence, $y_{i,t}$	Fifty-Year Change in Conflict Incidence, $\Delta y_{i,d\text{-}5}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
									Avg Temp, 1401-1450	
						Baseline			<= Median	> Median
Cooling:										
$\Delta C_{i,d\text{-}5}$		0.0477***	0.0468***	0.0650***	0.0426***	0.0436***	0.0269*	0.0430**	0.0437	0.0461
		(0.0155)	(0.0157)	(0.0241)	(0.0141)	(0.0146)	(0.0142)	(0.0178)	(0.0267)	(0.0296)
$\Delta C_{i,d\text{-}5}^2$			-0.0186	-0.0237						
			(0.0203)	(0.0206)						
$\Delta C_{i,d\text{-}5}^3$				-0.0521						
				(0.0328)						
$\Delta C_{i,d\text{-}5} \times \Delta C_{i,d\text{-}10}$					0.0859**	0.0874**	0.0878**	0.0892**	0.181**	0.0455
					(0.0372)	(0.0386)	(0.0384)	(0.0380)	(0.0719)	(0.0494)
$\Delta C_{i,d\text{-}10}$					0.00101	0.00344	0.00126	0.0140	0.00296	-0.0101
					(0.0125)	(0.0130)	(0.0132)	(0.0165)	(0.0315)	(0.0219)
Temperature:										
$T_{i,d}$	-0.0299***						-0.0372**	-0.0307		
	(0.0087)						(0.0173)	(0.0224)		
$T_{i,d\text{-}10}$								-0.0312*		
								(0.0161)		
Grid-Cell FE	Y	Y	Y	Y	N	Y	Y	Y	Y	Y
Time Period FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	14,000	12,880	12,880	12,880	11,480	11,480	11,480	11,200	5,740	5,740
Number of Clusters	280	280	280	280	280	280	280	280	140	140
R-squared	0.291	0.016	0.016	0.016	0.014	0.017	0.017	0.018	0.022	0.021
Marginal effect of cooling with 1C of cooling in the previous 50-year period ($\Delta C_{i,d\text{-}5}+\Delta C_{i,d\text{-}5} \times \Delta C_{i,d\text{-}10}$):										
Coeff					0.129	0.131	0.115	0.132	0.224	0.092
S.E.					(0.040)	(0.041)	(0.041)	(0.040)	(0.088)	(0.049)

Notes: The unit of observation is a decade and a 400 km by 400km grid-cell. Coefficients are reported with standard errors clustered at the grid-cell level in parentheses.

standard-deviation increase in cooling (a change of 0.23 degrees Celsius) increases the change in conflict incidence by $0.23 \times 0.0477 = 0.011$ or 1.1 percentage-points. This effect is significant given that the mean of the change in conflict incidence is -0.00047 and the standard deviation is 0.34.

Given that the relationships between temperature and outcomes such as agricultural production and mortality can be highly non-linear (e.g., Schlenker and Roberts, 2009; Deschenes and Greenstone, 2011), we check for non-linearities by adding higher-order terms for cooling to equation (3). The results, reported in columns (3) and (4) of Table 1, show that the higher-order terms add little to the explanatory power. Their coefficients are small in magnitude and statistically insignificant, and the R-squared of the equation remains virtually unchanged.

We now turn to our primary question of interest, which is whether the effect of cooling on the change in conflict incidence depends on a location's earlier cooling. We do this by estimating equation (4), which includes a measure of cooling in the preceding fifty-year period, as well as its interaction with cooling during the current fifty-year period. The estimates are reported in columns (5) and (6) of Table 1. Column (5) reports a specification without grid-cell fixed effects, while column (6) reports a specification that also includes grid-cell fixed effects. The two specifications produce nearly identical estimates.[19] According to the baseline estimates in column (6), a one-degree decline in temperature during the current fifty-year period (that was not preceded by earlier cooling) increases the change in conflict incidence over the same period by 4.36 percentage-points. This finding is consistent with the estimate from column (1), showing that lower temperatures increase conflict incidence. By contrast, a one-degree decline in temperature during the previous fifty-year period (50 to 100 years prior) has no direct effect on conflict change over the subsequent fifty-year period. The estimated coefficient is statistically insignificant and very small in magnitude. Thus, although cooling during a fifty-year period has a contemporaneous effect on conflict in that period, it has no lagged effect on conflict during the next fifty-year period.

The estimates also show that the coefficient on the interaction term is large, positive, and statis-

[19] This is because average changes in temperature and conflict incidence over time are around zero across cells (i.e., temperature and conflict cycles over our very long time horizon of 500 years). Recall the discussion in the data section.

tically significant. It shows that the effect of cooling on conflict change during the current period is significantly greater if the location also experienced cooling in the previous fifty-year period. According to the estimates, if the location experienced a degree more of cooling in the previous fifty-year period, then the effect of a degree of cooling in the current period on the increase in conflict will be 8.74 percentage-points greater. These estimates provide evidence for the presence of intensification effects, and their dominance over any adaptation effects, if they exist. The significant (and large) interaction effect also suggests that standard models that only allow for contemporaneous effects of cooling (or climate change more generally) on conflict incidence are potentially misspecified. Even if the models allow for lagged effects, where past periods of cooling to have an effect, they still may be misspecified. This is because the primary effect of past periods of cooling appears not to be through a direct persistent effect, but through an indirect effect on the impact that subsequent shocks have on the outcome of interest.

At the bottom of Table 1, we report the estimated effect (and standard error) of cooling during the current fifty-year period on conflict change during the same period if there was one-degree of cooling in the previous fifty-year period, i.e., $\alpha_1 + \beta \cdot 1$. According to our baseline estimate from column (6), if a location experienced one-degree Celsius of cooling in the previous fifty-year period, then a degree of cooling this period increases conflict incidence by 13.1 percentage-points. If the same location did not experience any cooling in the previous fifty-year period, then the same effect would only be 4.36 percentage-point increase (i.e., α_1).

To further assess the magnitude of the estimate, consider a one-standard-deviation increase in cooling, which is equal to 0.227 degrees Celsius. Also, recall that a standard deviation of a change in conflict incidence is 0.34, or 34 percentage-points. According to our estimates, a one-standard-deviation increase in cooling, but with no cooling in the previous period, is associated with an increase in conflict incidence of just under one percentage-point ($0.0436 \times 0.227 = .0099$), which is equal to 0.03 standard deviations ($0.0099/0.339 = 0.29$). By contrast, a one-standard-deviation increase of cooling, with a standard deviation of cooling in the previous period, is associated with an increase in conflict incidence of 2.97 percentage-points ($(0.0436 \times 0.227) + (0.0874 \times 0.227) =$

0.0297), which is equal to 0.09 standard deviations ($0.0297/0.339 = 0.087$). Thus, these magnitudes are sizable, but at the same time plausibly moderate since we believe that many other factors determined the overall variation in conflict in our sample.

In column (7), we introduce a control for the average temperature during the last decade of the observation, decade d. This addresses the concern that the extent of cooling is mechanically associated with the level of temperature at the end of the fifty-year period. If the level of temperature itself affects changes in conflict incidence, then this could confound our estimated impact of cooling on conflict. The estimates show that the interaction coefficient of interest remains robust to the inclusion of a control for the average temperature measured at the end of the fifty-year time-period. In column (8), we add a control for the average temperature at the beginning of the one-hundred-year period. This addresses the concern that the degree of cooling may have been correlated with initially cooler temperature levels, and conflict may have evolved differently depending on initial conditions. The estimates show that the main results remain robust to the inclusion of this control.

Finally, we examine heterogeneity by a location's average temperature, measured during our base time-period, 1401-1450. This specification is motivated by studies, such as Dell et al. (2012), Waldinger (2015), and Burke and Emerick (2015), that investigate whether the relationship between temperature and outcomes differ according to temperature in a base-period.[20] This also tests our conjecture that the adverse effects of cooling may be driven by places that were initially cold (relative to optimal growing conditions) getting colder. We divide the sample into two equally sized groups depending on whether the baseline temperature is above or below the median. The estimates for the two samples are reported in columns (9) and (10) of Table 1. While the baseline effect of cooling on the change in conflict incidence α_1 is similar in both samples, the coefficient of the interaction term, β, which captures the net of adaptation-intensification effects, is much larger in magnitude and only significant for the locations that were initially colder. In addition, as shown at the bottom of the table, the estimated effect of cooling, conditional on cooling in the previous decade is much larger in the initially colder locations. Thus, the effects of cooling on increased

[20]Our exercise differs slightly from theirs since we are examining whether the effect of temperature change, rather than temperature levels, varies by baseline temperature.

Table 2: The Correlates of Cooling

		(1)	(2)
		Dependent Variable	
	Independent Variable	$\Delta C_{i,d-5}$	$\Delta C_{i,d-5} \times \Delta C_{i,d-10}$
A.	Incidence of Conflict (1401--1450)	-0.00196	0.00949*
B.	Interstate Conflict Incidence (1401--1450)	-0.00148	0.00642
C.	Civil Conflict Incidence (1401--1450)	-0.00394	0.00684*
D.	Average Number of Conflicts (1401--1450)	-0.00305	0.00444
E.	Average Temperature (1401--1450)	0.125***	-0.00263
F.	Number of Cities (1400)	-0.00380	0.00424
G.	Suitability for Wheat, Dry Rice, Wet Rice, Barley, and Rye (1st P.C.)	-0.0458***	0.00575
H.	Suitability for Potatoes	-0.0464***	0.00320
I.	Latitude	0.0261***	-0.0576***
J.	Longitude	-0.0886***	0.0190
K.	Distance to the Coast	-0.101***	-0.0226***
L.	Slope	-0.0162**	0.00569
M.	Elevation	-0.0173	-0.0141

Notes: The unit of observation is a 400km by 400km grid cell and decade. Each cell reports the correlation coefficient between the variable listed in the column heading and the variable listed in the row heading. The bivariate correlations reported in column (1) each have 12,880 observations, while the correlations reported in column (2) each regression has 11,480 observations. The standard errors are clustered at the cell level. *, ** and *** indicate significance at the 10%, 5% and 1% levels.

conflict are primarily driven by places that were cold to begin with.

5.3 Robustness

5.3.1 Correlates of Conflict and Cooling

Since most of the climate change in our context is not believed to be a result of human actions (Mann, 2002, p. 508), our main empirical concern is that cooling happened to occur in places that had other features that caused them to experience different patterns of conflict over time – i.e., the presence of spurious correlations. To address this concern, we control for variables that are potentially correlated with either climate change or conflict and allow their effects to differ flexibly over time. As a first step, we first examine the relationships between a number of potentially important time-invariant covariates and our two independent variables of interest, the extent of cooling during a fifty-year period $\Delta C_{i,d-5}$, and the interaction of this with the extent of cooling in the prior fifty-year period, $\Delta C_{i,d-5} \times \Delta C_{i,d-10}$. Table 2 reports the bivariate relationship between the two variables and a range of time-invariant covariates.

The correlation coefficient reported in row A of column (1) shows that cooling is unrelated to the incidence of conflict in the first period of our panel, 1401-1450. We can also classify conflicts according to the type of war that they were a part of, either inter-state or intra-state. As shown in column (1) of rows B and C, the incidence of either type of conflicts during the base period is unrelated to cooling. Alternatively, we can examine the number of conflicts instead of incidence during the base period. We find that this too is uncorrelated with cooling (row D). Looking at average temperature in 1401-1450, we find that subsequent cooling is positively correlated with initial temperature. Places that experienced more cooling were initially warmer (row E). We also consider economic development in our initial period, as measured by the number of cities present. Using georeferenced data from Nunn and Qian (2011) on city location and size, we compute the number of cities per grid-cell in 1400. We find that this is uncorrelated with cooling (row F).

We examine the relationship between agricultural suitability and cooling by using measures of crop suitability from the FAO GAEZ dataset. We use Old World staple crops that existed prior to the Columbian Exchange (wheat, dry rice, wet rice, barley and rye). We also measure potatoes separately, which were an important staple introduced as a field crop first adopted in Europe in the late 17th and early 18th centuries (Nunn and Qian, 2010, 2011). Because of the high correlation across suitability for the five staple crops, we use the first principal component of the suitability measures.[21] We find that places that experienced more cooling were also those that were less suitable for the cultivation of Old World staple crops and potatoes (rows G and H).

Finally, we examine geographic characteristics that could be correlated with cooling: latitude, longitude, distance to the nearest coastline, slope and elevation (rows I to M). The correlates show that northern and western regions in our sample experienced more cooling. Given the geographic shift in conflict from north to south that we observed earlier in Section 4, this raises the important concern that not accounting for latitude may cause our baseline estimates to be confounded. The correlations also show that regions closer to the coast and regions that are flatter experienced more cooling. This pattern of cooling could confound our estimates if coastal areas or regions with flatter

[21] See the Data Appendix for a description of the FAO data. The first principal component is the only component to have an eigenvalue of more than one. Iyigun et al. (2016) use a similar measure.

terrain experienced other changes during cooling periods that could have influenced conflict. Over the long time horizon that we study, we are most concerned about the many changes in military technologies that may have changed the costs and benefits of fighting over certain types of terrain.

Column (2) reports the bivariate relationships between the same set of variables and the interaction of cooling in two consecutive fifty-year periods. The variables that are significantly correlated are the incidence of conflict during 1401-1450, the incidence of civil conflict during 1401-1450, latitude, and distance to the coast.

To address the concern that the estimated effect of cooling on conflict change may be confounded by these other factors, Table 3 reports estimates of equation (4) controlling for the set of covariates reported in Table 2, each interacted with decade fixed effects, which allows the influence of the additional control variables to vary flexibly over time. To be cautious, we control for all covariates, not just the ones that are significant in Table 2.[22] In column (1), we reproduce the baseline estimates for comparison, and in columns (2)-(7), we report the estimates with the additional covariates. We find that the estimates of interest remain robust. Thus, it is unlikely that our main results are driven by spurious correlations.

In column (8), we control for a lag of the dependent variable to address the possibility that conflict change may persist over time for reasons other than cooling.[23] Our equation includes measures of cooling during the current and previous fifty-year period ($t-49$ to t and $t-99$ to $t-50$). Since the change in conflict during the previous fifty-year period ($t-99$ to $t-50$) is endogenous to cooling that period, we do not control for conflict change during this time. Instead, we control for the lagged change conflict incidence from two periods ago ($t-149$ to $t-100$). As reported, the estimates remain robust to the inclusion of this covariate.

Finally, in columns (9) and (10), we show the robustness of our standard errors to alternative

[22] In column (5), we control for the suitability for the cultivation of Old World staples interacted with time period fixed effects and the suitability for potato cultivation interacted with a post-1700 dummy variable. The latter control is motivated by the fact that potatoes were not cultivated as an important field crop until the end of the 1600s (Nunn and Qian, 2011).

[23] The conflict literature at large typically worries that the mechanical persistence in conflict levels can confound causal estimates, and the typical way to deal with this is to control for lagged conflict levels. Ex ante, this is less obvious of a concern for our examination of changes. Note that a common problem in controlling for a lagged dependent variable in a short panel is the Nickel Bias. The length of our panel mitigates this concern.

methods for calculating standard errors. In column (9), we report standard errors clustered at the larger 800km$\times$800km grid-cell level. As we show, the use of larger clusters, which are approximately the size of modern France, has little effect on the standard errors. For some variables, the standard errors increase slightly, while for others they decrease slightly. In column (10), we report Conley (1999) standard errors adjusted for spatial autocorrelation, using a window of 10 degrees latitude and 10 degrees longitude. Again, the standard errors are similar to our baseline clustered standard errors.

5.3.2 Alternative Measures of Conflict

Following studies such as Miguel et al. (2004) and Dube and Vargas (2013), the analysis thus far examines conflict incidence as the outcome of interest. An alternative strategy is to measure conflict as the total number of conflicts (where a conflict is defined as a battle in location in a calendar year). Estimates where conflict is measured using the number of conflicts or the log number of conflicts are reported in Table 4.[24] Column (1) reproduces our baseline estimates for comparison, while columns (2) and (3) report the new estimates that use the number of conflict measures. As shown, the estimates are qualitatively similar across measures.

5.3.3 Measurement Error in Temperature

The historical temperature data are interpolated from underlying climate proxies. This raises the concern of measurement error. If the measurement error is classical, then the coefficients for the uninteracted variables will be biased towards zero. However, with classical measurement error, the sign of the bias for the coefficients of the interaction terms is ambiguous Griliches (1986); Klepper and Leamer (1984). Therefore, one concern is that the large positive interaction effect is a result of measurement error rather than intensification effects. We know of no obvious econometric method for dealing with this issue. Thus, we undertake a number of alternative strategies to address it. The first is to estimate equation (4) using three different 300-year sub-samples: 1401-1700, 1501-

[24]When we take the natural log of the total number of conflicts, we add 0.1 to the measure so that we do not lose observations with values of zero.

Table 3: The Effect of Cooling on Conflict: Robustness to Additional Control Variables

	Dependent Variable: Fifty-Year Change in Conflict Incidence, $\Delta y_{i,d-5}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline	Conflict Incidence 1401-1450 x Time FE	Number of Conflicts 1401-1450 x Time FE	Temperature 1401-1450 x Time FE	Suitability for Old World Staples x Time FE, Potatoes x post-1700	Number of Cities in 1400 x Time FE	Geographic Controls x Time FE	Accounting for Lagged Measure of Dependent Variable	Cluster Standard Errors at 800km by 800km Grid-Cell Level	Spatially-Adjusted Standard Errors
Cooling:										
$\Delta C_{i,d-5}$	0.0436***	0.0445***	0.0425***	0.0667***	0.0331*	0.0416***	0.1090***	0.0524***	0.0436**	0.0436**
	(0.0146)	(0.0145)	(0.0145)	(0.0244)	(0.0173)	(0.0146)	(0.0283)	(0.0178)	(0.0169)	(0.0174)
$\Delta C_{i,d-5}$ x $\Delta C_{i,d-10}$	0.0874**	0.0756**	0.0836**	0.1080**	0.0633*	0.0810**	0.1070*	0.0844**	0.0874**	0.0874**
	(0.0386)	(0.0355)	(0.0354)	(0.0422)	(0.0380)	(0.0376)	(0.0564)	(0.0401)	(0.0431)	(0.0428)
$\Delta C_{i,d-10}$	0.0034	0.0045	0.0040	0.0214	-0.0141	0.0035	0.0115	0.0042	0.0034	0.0034
	(0.0130)	(0.0126)	(0.0128)	(0.0247)	(0.0136)	(0.0130)	(0.0267)	(0.0131)	(0.0119)	(0.014)
Prior change in conflict, $\Delta y_{i,d-15}$								-0.0169		
								(0.0221)		
Grid-Cell FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time-Period FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	11,480	11,480	11,480	11,480	11,029	11,480	11,480	10,080	11,480	11,480
Number of Clusters	280	280	280	280	269	280	280	280	85	n/a
R-squared	0.017	0.043	0.043	0.019	0.031	0.032	0.041	0.019	0.017	0.017
Marginal effect of cooling with 1C of cooling in the previous 50-year period ($\Delta C_{i,d-5}+\Delta C_{i,d-5}$ x $\Delta C_{i,d-10}$):										
Coeff	0.131	0.120	0.126	0.175	0.096	0.123	0.216	0.137	0.131	
S.E.	(0.041)	(0.038)	(0.038)	(0.048)	(0.042)	(0.040)	(0.061)	(0.043)	(0.048)	

Notes: The unit of observation is a decade and a 400km by 400km grid cell. "Geographic Controls" (in column 7) include: latitude, longitude, elevation, slope and the distance to the nearest coast. Coefficient are reported with standard errors clustered at the grid-cell level in parentheses, except for column (9), where the standard errors are clustered at the 800km by 800km grid-cell level, and column (10) where we report Conley standard errors adjusted for spatial autocorrelation with a window of 10 degrees latitude and 10 degrees longitude.

Table 4: The Effect of Cooling on Conflict: Robustness to Alternative Measure of Conflict

	Dependent Variable: Fifty-Year Change in Conflict Measure		
	(1)	(2)	(3)
	Conflict Incidence (Baseline)	Total Number of Conflicts	Natural Log of Total Number of Conflicts
Cooling:			
$\Delta C_{i,d-5}$	0.0436***	0.0128	0.1140***
	(0.0146)	(0.0502)	(0.0405)
$\Delta C_{i,d-5} \times \Delta C_{i,d-10}$	0.0874**	0.218*	0.244**
	(0.0386)	(0.131)	(0.109)
$\Delta C_{i,d-10}$	0.0034	0.0408	0.0177
	(0.0130)	(0.0290)	(0.0349)
Grid-Cell FE	Y	Y	Y
Time Period FE	Y	Y	Y
Observations	11,480	11,480	11,480
Number of Clusters	280	280	280
R-squared	0.017	0.020	0.020
Marginal effect of cooling with 1C of cooling in the previous 50-year period ($\Delta C_{i,d-5}+\Delta C_{i,d-5} \times \Delta C_{i,d-10}$):			
Coeff	0.131	0.231	0.357
S.E.	(0.041)	(0.111)	(0.116)

Notes: The unit of observation is a decade and a 400km by 400km grid-cell. Coefficients are reported with standard errors clustered at the grid-cell level in parentheses.

1800, and 1601-1900. The estimates from this exercise are informative since more recent periods have higher quality temperature data due to the fact that the number of underlying weather proxies increases steadily over time (Mann et al., 2009a). Thus, we check the sensitivity of our results to the use of data from the different time periods. The estimates are reported in columns (2)-(4) of Table 5. In column (1), the baseline estimates are reproduced for comparison. The results show that the estimates are similar across the three subsamples, which indicates that differences in the quality of the temperature data over time do not have a strong effect on our estimates of interest.

The second strategy that we undertake restricts our sample to observations that are less likely to contain significant measurement error due to the presence of a climate proxy (i.e., the raw data) in that grid-cell. Specifically, we omit grid-cells for which there are no underlying climate proxies in the Mann et al. dataset. The estimates are reported in columns (5) and (6) of Table 5. Column (5) presents estimates after restricting the sample to only include grid-cells that have at least one climate proxy in any time period. Column (6) further restricts the sample to observations (i.e., grid-cells and

Table 5: The Effect of Cooling on Conflict: Robustness to Alternative Samples

	Fifty-Year Change in Conflict Incidence, $\Delta y_{i,d-5}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		300-Year Subsamples				Grid-Cells and Time-Periods with Climate Proxies	Omit Cells with Documentary Proxies
	Full Sample	1401-1700	1501-1800	1601-1900	Grid-Cells with Climate Proxies		
Cooling:							
$\Delta C_{i,d-5}$	0.0436***	0.0203	0.0376**	0.0482***	0.0927*	0.0946	0.0446***
	(0.0146)	(0.0175)	(0.0160)	(0.0179)	(0.0526)	(0.0591)	(0.0148)
$\Delta C_{i,d-5}$ x $\Delta C_{i,d-10}$	0.0874**	0.110**	0.0809**	0.101**	0.202*	0.149	0.0903**
	(0.0386)	(0.0436)	(0.0393)	(0.0438)	(0.115)	(0.122)	(0.0366)
$\Delta C_{i,d-10}$	0.00344	-0.0191	0.00828	0.0143	-0.00516	0.000299	0.00796
	(0.0130)	(0.0201)	(0.0141)	(0.0179)	(0.0329)	(0.0375)	(0.0131)
Observations	11,480	5,880	8,400	8,400	2,255	1,984	11,349
Number Clusters	280	280	280	280	55	55	279
R-squared	0.017	0.018	0.014	0.023	0.049	0.060	0.016
Marginal effect of cooling with 1C of cooling in the previous 50-year period ($\Delta C_{i,d-5}+\Delta C_{i,d-5}$ x $\Delta C_{i,d-10}$):							
Coeff	0.131	0.130	0.119	0.149	0.295	0.244	0.135
S.E.	(0.041)	(0.043)	(0.042)	(0.047)	(0.115)	(0.123)	(0.039)

Notes: The unit of observation is a decade and a 400km by 400km grid-cell. Coefficients are reported with standard errors clustered at the grid-cell level in parentheses.

time-periods) that have at least one climate proxy in that grid-cell and time period. Both restrictions result in a significantly smaller sample size and reduction in power, and thus the standard errors for all coefficients increase noticeably. This said, the point estimates remain robust. In particular, the coefficient on our interaction term (our primary variable of interest) remains positive and large in magnitude. Since we expect there to be less measurement error in the restricted samples used in columns (5) and (6), the results suggest that it is unlikely that the estimate for the interaction effect from the baseline specification reported in column (1) is biased upwards due to measurement error.

As a final strategy, we address the concern that extent and nature of documentary evidence for temperature may be endogenous to the conflict. Relative to other datasets, such as Luterbacher et al. (2004), the data from Mann et al. (2009a) uses very little documentary evidence. However, to be as conservative as possible, we omit cells with documentary proxies. Column (7) shows that this has little effect on the estimates.

5.3.4 Spurious Correlation with Large Wars

Given that our analysis examines the incidence of conflicts (i.e., battles) and not wars (which comprise many battles), one may be concerned that our results are spuriously driven by a small number of large wars that included many conflicts. To address this, we alternately omit the 25 largest wars from our sample when constructing our conflict incidence indicator variable. The largest war contains 74 battles and the 25th largest war contains 18 battles. Appendix Table A.1 shows that our estimates remain robust to the exclusion of any of the 25 largest wars. Thus, it does not appear that any particular large war is driving our results.

5.4 Heterogeneous Effects

Geography Although there are many potential explanations underlying our estimated relationship between cooling and conflict, the most natural one is that cooling resulted in reduced agricultural productivity and living standards, which in turn increased conflict.[25] To test for this mechanism, we check whether the effects we estimate vary by the extent to which locations were dependent on agriculture, which we measure in a variety of ways. The first is using agricultural productivity, measured using a grid-cell's average suitability for the cultivation of Old World staple crops (wheat, dry rice, wet rice, rye and barley).[26] We measure suitability as the first principal component of the suitability for these five crops. We divide the grid-cells into two groups according to whether it is above or below the sample median, and estimate equation (4) separately for the two samples. The estimates are reported in columns (1) and (2) of Table 6. As reported, the estimates reported in column (1) are smaller in magnitude and less precise than those in column (2). Although neither

[25] Indirect evidence of such a channel is provided by Iyigun et al. (2016), who show that the increase in agricultural productivity, that arose from introduction of the potato from the Americas during the Columbian exchange, resulted in decreased warfare and conflict.

[26] We measure suitability for the cultivation of potatoes using the suitability index (ranging from 0 to 100) from the most recent version of the Food and Agricultural Organization's (FAO's) *Global Agro-Ecological Zones* (GAEZ) database (accessed October 31, 2014). The FAO predicts the suitability of locations for the cultivation of a number of important crops based on time-invariant natural conditions (i.e., conditions that are unlikely to change over time such as the average days of sunshine), and which allow us to specify inputs to simulate historical technologies (e.g. rain-fed irrigation). The original database is at an (approximately) 10km resolution. We construct averages within our grid-cells and use this measure.

Table 6: The Effect of Cooling on Conflict: Heterogenous Effects According to Geography

	Dep Var: Fifty-Year Change in Conflict Incidence, $\Delta y_{i,d-5}$					
	Suitability for Old World Staples (First P.C.)		Distance to Coast		Number of Cities in 1400	
	(1)	(2)	(3)	(4)	(5)	(6)
	<= Median	> Median	<= Median	> Median	None	One or more
Cooling:						
$\Delta C_{i,d-5}$	0.0212	0.0771**	0.0354*	0.1130**	0.0414***	0.208
	(0.0141)	(0.0374)	(0.0179)	(0.0516)	(0.0158)	(0.202)
$\Delta C_{i,d-5}$ x $\Delta C_{i,d-10}$	0.0127	0.206	0.0691	0.0853	0.0728**	0.595
	(0.0210)	(0.126)	(0.0514)	(0.0785)	(0.0361)	(0.473)
$\Delta C_{i,d-10}$	-0.00290	-0.00269	-0.0179	0.0372	0.00263	0.0617
	(0.00960)	(0.0280)	(0.0158)	(0.0383)	(0.0129)	(0.1050)
Observations	4,860	5,220	4,860	5,220	9,108	972
Number Clusters	135	145	135	145	253	27
R-squared	0.023	0.031	0.020	0.033	0.015	0.091
Marginal effect of cooling with 1C of cooling in the previous 50-year period ($\Delta C_{i,d-5}+\Delta C_{i,d-5}$ x $\Delta C_{i,d-10}$):						
Coeff	0.034	0.283	0.105	0.199	0.114	0.803
S.E.	(0.023)	(0.143)	(0.060)	(0.068)	(0.038)	(0.530)

Notes: The unit of observation is a decade and a 400km by 400km grid-cell. Coefficients are reported with standard errors clustered at the grid-cell level in parentheses.

of the coefficients for the interaction terms are statistically significant at conventional levels, the magnitude of the estimates show that the effects of cooling (with or without prior cooling) appear to be driven by locations that are more suitable for agriculture.[27]

The second characteristic that we consider is distance to the coast. Since areas closer to the coast are, on average, more integrated and involved in long-distance trade and commerce, we expect them to be less dependent on regional agriculture. We calculate the distance from the center of each grid-cell to the nearest coastline and divide the sample into grid-cells that are above or below the median value. Columns (3) and (4) in Table 6 show that the effects are qualitatively similar between coastal and inland regions, but the magnitude of the effect of cooling on conflict (with or without prior cooling) is larger for inland regions. This is consistent with the coastal areas being less sensitive to negative shocks to agricultural productivity because of their specialization in trade and commerce.

[27]Note that in principle, we can also test for differences in effects depending on whether a location was suitable for the cultivation of staples that are better able to survive in cold climates, namely rye, barley, and potatoes (which were introduced during the Columbian Exchange). These results are available upon request and very similar to those in columns (1) and (2). We believe that the similarity is partly due to the high correlation between agricultural productivity across different crops, and thus we learn little from comparing the two sets of estimates and do not present them in the paper.

We next examine the differential effects for grid-cells that were more or less urbanized at the beginning of our period of interest. Cities, like coastal locations, are less dependent on agriculture since they are more specialized in commerce and manufacturing. We divide the sample according to whether or not a grid-cell contained any cities in 1400, where a city is defined as a location with more than 40,000 inhabitants. In our sample, only 8.7% of grid-cells contained a city in 1400. Thus, the sample size for grid-cells with cities is much larger than that the sample size for grid-cells without cities. The estimates are reported in columns (5) and (6) of Table 6. Although both estimates are positive, the magnitude of the estimated impact of cooling on conflict (with or without prior conflict) is much larger for grid-cells with cities in our base time-period. The estimates for the urban cells are statistically insignificant, which is not surprising given the small sample size. The estimates for the non-city sample are statistically significant, but much smaller in magnitude. The relative magnitudes of the coefficient estimates could be due to the fact that conflict tends to occur where populations are located and therefore the marginal effect of climate change on conflict is greater in cells with urban locations. However, the point estimates should be interpreted with caution given the large standard errors around the point estimates for the urban sample.

Type of Wars We next examine whether the effects differ across different forms of war, either wars between two different nation states (an inter-state war) or a war that involves a state and a domestic non-state actor (an intra-state war). We divide conflicts into those that are part of an intra-state war and those that are part of an inter-state war, and construct separate conflict incidence measures for both types of conflicts. The estimates with both types of conflict incidence as the dependent variable are reported in columns (1) and (2) of Table 7. We find that the estimates are qualitatively similar for both types of conflicts. The coefficients for cooling in the contemporaneous period are positive and statistically significant. The interaction coefficient is always positive and large in magnitude, but less precisely estimated for inter-state conflicts. The effect of cooling in the previous fifty-year period is small in magnitude and statistically insignificant for both types of conflict. The marginal effect shown on the bottom of the table is positive and significant for both

Table 7: The Effect of Cooling on Conflict: Heterogenous Effects Depending on Characteristics of the War

	Dep Var: Fifty-Year Change in Conflict Incidence, $\Delta y_{i,d-5}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	War Type		War Size (Number of Battles)			Border in Cell in 1450	
	Intra-State	Inter-State	Small	Medium	Large	None	Border
Cooling:							
$\Delta C_{i,d-5}$	0.0132	0.0248**	0.00422	0.0202*	0.0119	0.0117	0.101***
	(0.00835)	(0.0114)	(0.00915)	(0.0104)	(0.00783)	(0.00893)	(0.0357)
$\Delta C_{i,d-5}$ x $\Delta C_{i,d-10}$	0.0369*	0.0534	-0.00465	0.0961***	0.00341	0.0341	0.0930
	(0.0222)	(0.0370)	(0.0210)	(0.0330)	(0.0194)	(0.0217)	(0.0965)
$\Delta C_{i,d-10}$	-0.00772	0.0121	-0.0132	-0.0152*	0.0365***	0.00109	0.0126
	(0.00954)	(0.0136)	(0.0102)	(0.00905)	(0.00865)	(0.00875)	(0.0314)
Observations	11,480	11,480	11,480	11,480	11,480	5,330	6,150
Number Clusters	280	280	280	280	280	130	150
R-squared	0.020	0.018	0.010	0.018	0.037	0.014	0.025
Marginal effect of cooling with 1C of cooling in the previous 50-year period ($\Delta C_{i,d-5}+\Delta C_{i,d-5}$ x $\Delta C_{i,d-10}$):							
Coeff	0.050	0.078	0.000	0.116	0.015	0.046	0.194
S.E.	(0.022)	(0.040)	(0.022)	(0.035)	(0.018)	(0.022)	(0.100)

Notes: The unit of observation is a decade and a 400km by 400km grid-cell. Coefficients are reported with standard errors clustered at the grid-cell level in parentheses.

types of conflicts. The magnitude is larger for interstate conflicts, but the difference in magnitude between the two types of conflict is not statistically significant. The similarity of the estimates is consistent with historical accounts that report that cooling was associated with increased conflicts of all types.

We also check for differential effects depending on the size of the war a conflict belongs to. We do this by dividing conflicts into three equally-sized groups (i.e., the same number of conflicts in each group) according to whether a conflict belonged to a small, medium, or large sized war, where the size of the war is measured by counting the number of battles that are associated with the war.[28] We then construct our three conflict incidence measures, one for each size of war. The estimates with these three measures as the outcome of interest are reported in columns (3)-(5) of Table 7. Interestingly, the estimates show that the main results are primarily due to the impacts on medium

[28]The raw conflict data report fatalities, but only for some battles. This statistic is not systematically reported.

sized wars (and to some extent large wars).

Political Fractionalization We next examine whether regions that were politically more fractionalized *ex ante* were more sensitive to the impacts of cooling on conflict. To examine this, we divide observations into two groups based on whether a grid-cell contained a border at any point from 1401-1450. On average, almost half of the observations contain a border in the base time period.[29] The estimates, which are reported in columns (6) and (7) of Table 7, show that the effects are qualitatively similar for the two samples. However, the magnitude is larger in grid-cells that were split by a borders in the initial period. These results are consistent with regions with higher fractionalization being more sensitive to climate change.

6 The Very Long-Run Effects of Cooling on Conflict

In this section, we take advantage of the length of our panel data to estimate the potential for longer-run adaptation or intensification effects. In doing this, we allow the impact of cooling during the current fifty-year period on conflict change during the same fifty-year period to depend on cooling over the previous four fifty-year time periods, rather than just the one previous fifty-year period. It is possible that periods of cooling prior to the previous fifty-years also matter. Thus, our estimating equation is:

$$\begin{aligned}\Delta y_{i,d-5} = &\sum_{k\in K_5} \alpha_k(\triangle C_{i,d-k}) + \sum_{k\in K_{10}} \beta_{5,k}(\triangle C_{i,d-5} \times \triangle C_{i,d-k}) \\ &+ \sum_{k\in K_{15}} \beta_{10,k}(\triangle C_{i,d-10} \times \triangle C_{i,d-k}) + \sum_{k\in K_{20}} \beta_{15,k}(\triangle C_{i,d-15} \times \triangle C_{i,d-k}) \\ &+ \beta_{20,25}(\triangle C_{i,d-20} \times \triangle C_{i,d-25}) + X_{i,d}\Gamma + \rho_i + \delta_d + \varepsilon_{i,d},\end{aligned} \tag{5}$$

where K_5, K_{10}, K_{15}, and K_{20} denote the following sets of numbers: $K_5 = \{5, 10, 15, 20, 25\}$, $K_{10} = \{10, 15, 20, 25\}$, $K_{15} = \{15, 20, 25\}$, and $K_{20} = \{20, 25\}$. k indexes the numbers within

[29]We digitized data on borders for every fifty years. These are reported by Reed, Frank E. *Centennial Historical Atlas*. Clockwork Software Incorporated, 2014. http://www.historicalatlas.com.

the set.

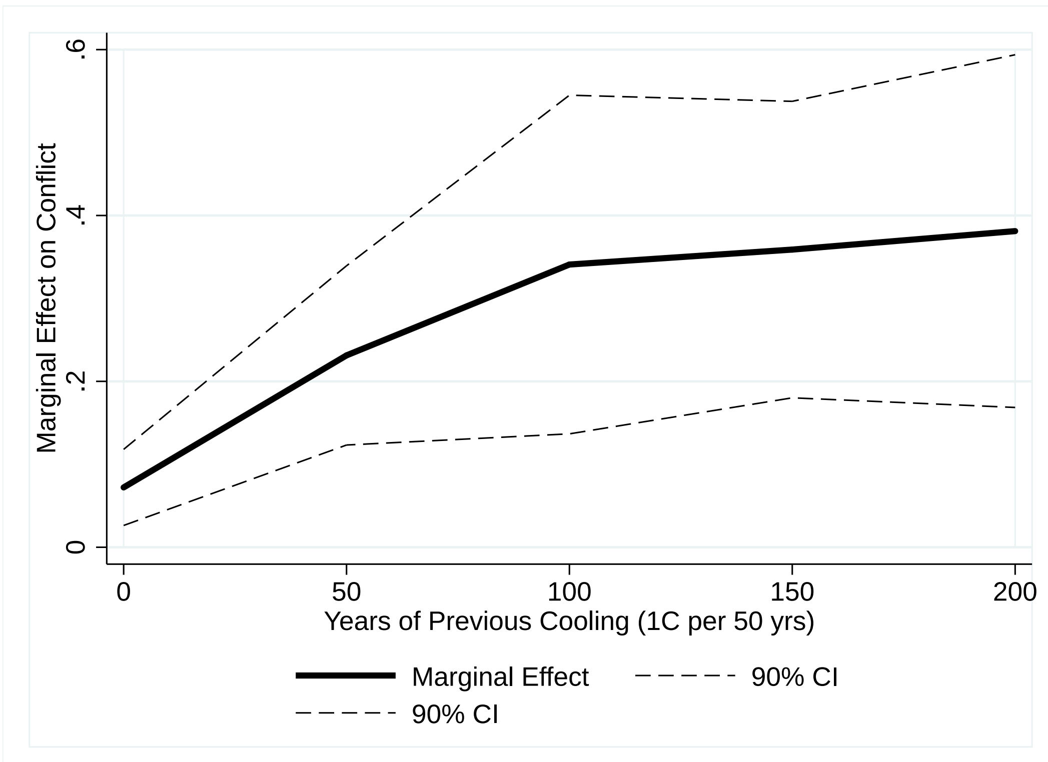
By including interactions that involve $\Delta C_{i,d-5}$, e.g., $\Delta C_{i,d-5} \times \Delta C_{i,d-10}$, $\Delta C_{i,d-5} \times \Delta C_{i,d-15}$, etc, equation (5) allows intensification and adaptation effects to occur over longer periods of time. The estimates of the coefficients $\beta_{5,k}$ capture how the impact of cooling in the current period on conflict change in the same period is shaped by the history of cooling during the prior 200 years. The specification also includes the full set of lagged interaction terms, e.g., $\Delta C_{i,d-10} \times \Delta C_{i,d-15}$, $\Delta C_{i,d-15} \times \Delta C_{i,d-20}$, etc, which capture net adaptation and intensification effects that may have lagged impacts.

6.1 Flexible Estimate

The estimates of equation (5) are summarized in Figure 4, where we report the marginal effects of cooling on conflict change in the current period for different histories of cooling. The underlying estimates are reported in appendix Table A.2. The *x*-axis reports the number of previous years of cooling (at 1 degree Celsius per fifty-year period). At zero on the *x*-axis, we report the marginal effect of cooling without any cooling in previous periods. At 50 on the *x*-axis, we report the marginal effect of cooling when there was 1 degree of cooling during the previous fifty years. At 100, we report the marginal effect of cooling when there was 1 degree of cooling (per fifty-year period) during the previous 100 years. Analogously, at 150 and 200 on the *x*-axis, we report the marginal effects of cooling when there was one degree of cooling per fifty-year period during the previous 150 and 200 years, respectively. Also reported are the 90% confidence intervals of the estimated marginal effects.

We find evidence that intensification effects continue to dominate adaptation effects as cooling continues beyond 50 years prior. However, the magnitude of the intensification effects diminish with the duration of cooling. As with the main results, cooling during the most recent past fifty-year period (i.e., the previous fifty-year period) has a large influence on the marginal effect of contemporaneous cooling on increasing conflict change. However, cooling during earlier fifty-year periods (i.e., two or more fifty-year periods ago) has smaller influences. For example, having 200 years of

Figure 4: How the Marginal Effect of Contemporaneous Cooling on Conflict Change Varies Depending on Previous Periods of Cooling



Notes: The y-axis reports the marginal effects of cooling on conflict change in the current time period. The x-axis reports the number of previous years of cooling at one degree Celsius per fifty-year period. The calculated marginal effects are based on the estimated coefficients from equation (5), which are reported in table A.2 column (4).

prior cooling (at one degree per fifty years) has nearly the same impact on the marginal effect of contemporaneous cooling as 150 years of prior cooling, and only a slightly greater effect than 100 years of prior cooling. Thus, we find diminishing effects for the influence of past cooling on the marginal effect of contemporaneous cooling on conflict change.

Robustness To check that the very long-run estimates are not driven by spurious correlations, we include in equation (5) a similar set of geographic controls as reported in Table 3. We also control for temperature in the contemporaneous time period as in column (7) of Table 1. The estimates are reported in appendix Table A.3. The marginal effects – and how they vary with previous periods of cooling – are summarized in Figure 5. The estimates are very similar to the baseline estimates, which are shown by the thick solid black line. The estimated effects of cooling are always positive and tend to exhibit the same pattern as the baseline estimates. For all specification but two, the estimates are within the 90% confidence intervals of the baseline specification.

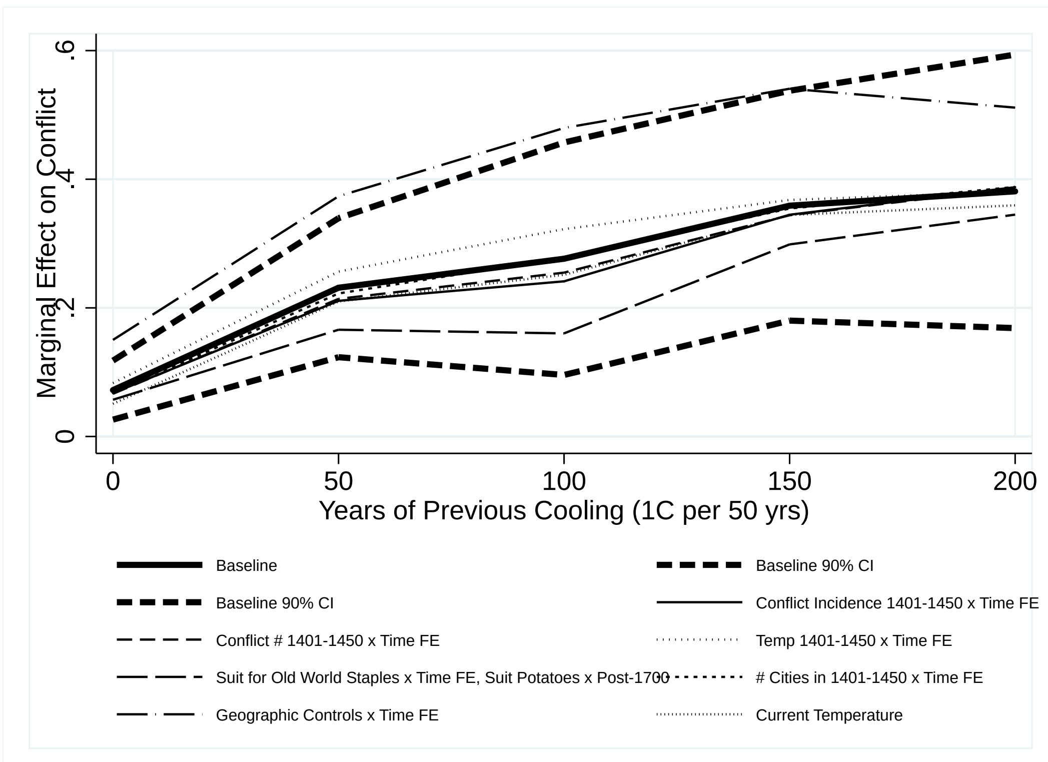
We also check that the very long-run estimates are not biased by our choice of the dependent variable. When we use alternative measures of conflict namely – the total number of battles and the natural log of the total number of battles – the predicted marginal effects are similar. These are shown in Figure 6.[30] Likewise, the precision of our estimates is similar if we conduct our analysis using larger grid-cells that are 800km by 800km in size. The estimates, which are reported in Appendix Figure A.1, are qualitatively identical to our baseline estimates which use 400km by 400km grid-cells.[31]

As a final exercise, we examine the best fit model by using LASSO. We undertake this exercise, with the caveat that LASSO is not designed for choosing the correct economic model, but the most parsimonious model that gives the best predictive power. Thus, the estimates should be interpreted with caution and we do not use LASSO to determine our main specification. We force the model to condition on time and grid-cell fixed effects. The LASSO-chosen model includes four lagged temperature changes and two interactions, including the most recent two lagged periods and

[30]The coefficients and standard errors are shown in Appendix Table A.4.

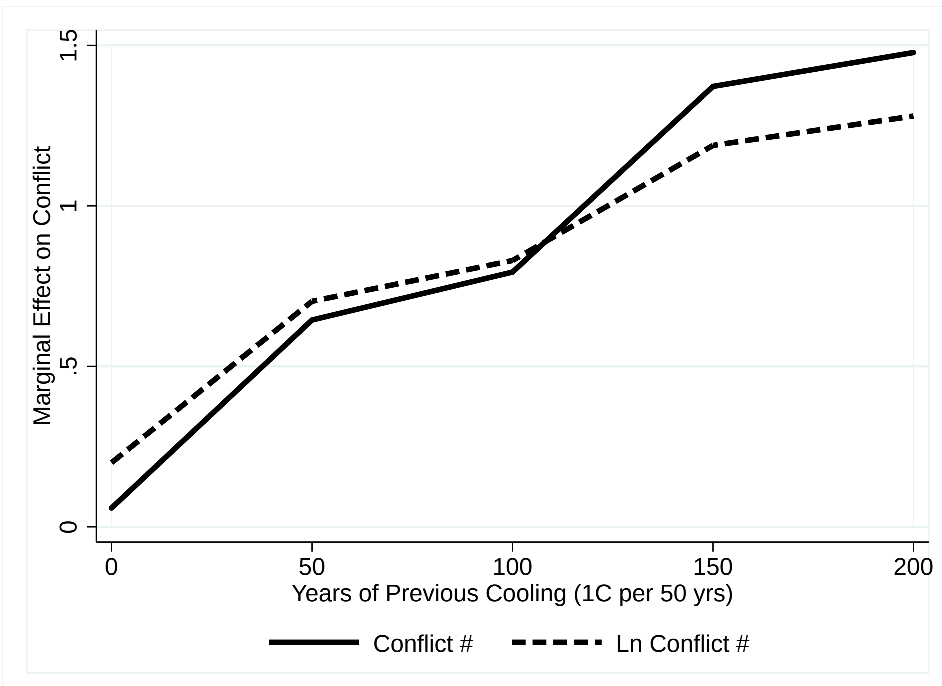
[31]Note that we do not check the robustness of our results to smaller grid-cell sizes since the climate data are not available at resolution finer than 5 arc minutes.

Figure 5: How the Marginal Effect of Contemporaneous Cooling on the Change in Conflict Incidence Depends on Previous Periods of Cooling: Robustness to Alternative Specifications



Notes: The *y*-axis reports the marginal effect of cooling on the change in conflict incidence. The *x*-axis reports the number of previous years of cooling at one degree celsius per fifty-year period. The reported effects are based on coefficient estimates from equation (5). The estimates are reported in Table A.3.

Figure 6: How the Marginal Effect of Contemporaneous Cooling on the Change in Conflict Incidence Depends on Previous Periods of Cooling: Robustness to Alternative Measures of Conflict



Notes: The *y*-axis reports the marginal effect of cooling on the change in conflict incidence. The *x*-axis reports the number of previous years of cooling at one degree celsius per fifty-year period. The reported effects are based on coefficient estimates from equation (5). The estimates are reported in appendix Table A.4.

their interactions (in addition to the imposed time-period and grid-cell fixed effects). The resulting pattern is similar to the baseline specification and is reported in Appendix Figure A.2.[32]

7 Policy Implications

Our empirical strategy offers several important advantages for understanding the effects of future climate change. In particular, by allowing past periods of cooling to affect the impacts of subsequent episodes of cooling, we are able to identify the presence of net adaptation or intensification effects. This is possible, in part, because we examine climate change over a very long period. An advantage of our strategy is that we do not rely on extrapolations from short-run estimates to obtain estimates of long-run effects. Our strategy provides alternative evidence for the long-run impacts of climate change, which is importance since, as Hsiang and Burke (2014) point out, historical data with "long time scales are able to examine 'low frequency' changes in climate that perhaps more closely resemble future anthropogenic climate changes".

At the same time, there are also several important caveats to bear in mind. First, the historical context, which is necessitated by the examination of changes over a long time horizon, differs from the modern context in ways that affect the speed of adaptation or the extent of intensification. In particular, better infrastructure and more trade can mitigate the effects of climate change (e.g., Burgess and Donaldson, 2010); that technological innovations, such as new seed varieties, may greatly reduce the medium-run impact of climate change (e.g., Emerick et al., 2015), and factors may be able to reallocate more quickly because modern economies have a greater share of workers in non-agriculture sectors (Waldinger, 2015). Second, within the historical setting that we examine, the adverse environmental disruption was due to cooling, whereas the environmental disruption in modern climate change is due to warming. Cooling and warming share similarities. For example, both are environmental changes that disrupt traditional economic activities. However, there is evidence from U.S. agriculture in the 20th century that cooling is less damaging to agricultural pro-

[32]Note that since the only interaction of current cooling chosen by the LASSO model is the interaction of current cooling with cooling during the previous period, the marginal effect is similar for cooling that lasts 100 years or longer.

ductivity than warming by the same magnitude (e.g., Schlenker and Roberts, 2009). If this is true more generally, then the effects of global warming on conflict may be larger than what is implied by our estimates.

Notwithstanding these caveats, our results provide new evidence and insights for policy makers who are interested in understanding and mitigating the adverse effects of future climate change. First, our results provide strong evidence for intensification effects and their dominance over any adaptation effects that may exist. We find that periods of climate change, in addition to having direct impacts in the contemporaneous period, also have important indirect impacts by magnifying the negative impacts of future climate change.

8 Conclusion

The long-run impact of climate change is one of the most important questions for policymakers and economists today. A large part of the debate revolves around how much society can adapt to climate change and how much time is required to adapt. At the same time, one worries that the effects of prolonged environmental disruption could cause institutions and state capacity to weaken, which could intensify the effects of environmental change. We make progress on these issues by examining the long-run historical impacts of climate change on conflict. To do this, we construct a large geo-referenced dataset on conflicts from 1400–1900 CE for Europe, North Africa and the Near East, and combine it with recently-constructed historical climate data.

Our decade-level panel enables us to estimate a flexible model that allows the impact of cooling to vary depending on a location's previous history of cooling. We find that climate change, which took the form of cooling during our period of analysis, significantly increased conflict. In addition, the estimated effect of cooling on the change in conflict differed depending on the history of cooling. The impacts of cooling during the current fifty-year period were greater if a location experienced more cooling during the previous fifty-year period. This finding provides new evidence for the presence of intensification effects.

To understand the policy implications for our results, it is important to point out some important similarities and differences between the historical context and the context of modern climate change. As we discussed in the introduction, cooling reduced agricultural production in our context while warming reduces production in the modern context. This is merely an artifact of the fact that historical climate change manifested as cooling in regions that were already cold, while modern climate change manifests as warming in equatorial regions that are already warm. Historical cooling in Europe and modern warming in equatorial regions share the fact that both disrupt traditional economic activities. Another important similarity is that the locations in our historical context and the equatorial countries in the modern context that suffer from climate change are both pre-industrial or early-industrial economies that rely heavily on agriculture, and have poor transportation and communication infrastructures that could facilitate the flow of the factors of production. Although the effects we estimate should be carefully interpreted as specific to our context, policymakers should take note of the insight that the effects of climate change can intensify with its duration.

Our study has several important implications for future studies of climate change. First, for studies of the long-run effects of climate change, it demonstrates the necessity of using flexible specifications that allow the effects of climate change to depend on the recent experience of a location. Second, our findings show that an important avenue for future research is to understand the mechanisms underlying intensification (and adaptation). Finally, our study demonstrates the benefits of using historical data to better understand long-run processes that are directly relevant for future economic development. We hope that the data that we have constructed, which will be made publicly available, will be useful to future researchers.

References

Anderson, Robert Warren, Noel D. Johnson, and Mark Koyama, "Jewish Persecutions and Weather Shocks: 1100–1800," *Economic Journal*, 2016, p. forthcoming.

Bai, Ying and James Kai-sing Kung, "Climate Shocks and Sino-nomadic Conflict," *Review of Economics and Statistics*, August 2011, *93* (3), 970–981.

_ and _ , "Climate Shocks and Sino-Nomadic Conflict," *Review of Economics and Statistics*, 2011, *93* (3), 970–981.

Besley, Timothy and Marta Reynal-Querol, "The Legacy of Historical Conflict: Evidence from Africa," *American Political Science Review*, 2014, *108* (2), 319–336.

Brecke, Peter, "Violent Conflicts 1400 A.D. to the Present in Different Regions of the World," 1999. Paper presented at the 1999 meeting of the Peace Science Society.

_ , "The Conflict Dataset: 1400 A.D.Present," forthcoming. Mimeo, Georgia Institute of Technology.

Burgess, Robin and Dave Donaldson, "Can Openness Mitigate the Effects of Weather Shocks? Evidence from India's Famine Era," *American Economic Review*, 2010, *100* (2), 449–53.

Burke, Marshall and Kyle Emerick, "Adaptation to climate change: Evidence from US agriculture," Stanford University Working Paper, Stanford University 2015.

_ , Solomon M. Hsiang, and Edward Miguel, "Climate and Conflict," *Annual Review of Economics*, 2015, *7* (1), 577–617.

Clodfelter, Micheal, *Warfare and Armed Conflicts: A Statistical Encyclopedia of Casualty and Other Figures, 1494-2007, 3rd Edition*, Jefferson, N.C.: McFarlane & Company Inc., 2008.

Conley, T. G., "GMM estimation with cross sectional dependence," *Journal of Econometrics*, September 1999, *92* (1), 1–45.

Dalgaard, Carl-Johan, Casper Worm Hansen, and Nicolai Kaarsen, "Climate Shocks and (Very) Long-Run Productivity," 2016. Mimeo, University of Copenhagen.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken, "Temperature Shocks and Economic Growth: Evidence from the Last Half Century," *American Economic Journal: Macroeconomics*, July 2012, *4* (3), 66–95.

_ , _ , and _ , "What Do We Learn from the Weather? The New Climate-Economy Literature," *Journal of Economic Literature*, 2014, *52* (3), 740–98.

Dencecco, Mark, "Fiscal Centralization, Limited Government, and Public Revenues in Europe," *Journal of Economic History*, 2009, *69* (1), 48–103.

_ and Mauricio Prado, "Warfare, Fiscal Capacity, and Performance," *Journal of Economic Growth*, 2012, *17* (3), 171–203.

Deschenes, Olivier and Michael Greenstone, "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US," *American Economic Journal: Applied Economics*, 2011, *3* (4), 152–85.

Dube, Oeindrila and Juan F. Vargas, "Commodity Price Shocks and Civil Conflict: Evidence from Colombia," *The Review of Economic Studies*, 2013.

Durante, Ruben, "Risk Cooperation and the Economic Origins of Social Trust: An Empirical Investigation," 2010. Working Paper, Sciences Po.

Emerick, Kyle, Manzoor H. Dar, Alain deJanvry, and Elisabeth Sadoulet, "Technological Innovations, Downside Risk, and the Modernization of Agriculture," Working Paper, University of California, Berkeley 2015.

Fagan, Brian, *The Little Ice Age: How Climate Made History, 1300-1850*, New York: Basic Books, 2000.

Fenske, James and Namrata Kala, "Climate and the Slave Trade," *Journal of Development Economics*, 2015, *112*, 19–32.

Findlay, Ronald and Kevin H. O'Rourke, *Power and Plenty: Trade, War, and the World Economy in the Second Millennium*, Princeton, NJ: Princeton University Press, 2007.

Griliches, Zvi, "Economic Data Issues," in Zvi Griliches and Michael D. Intriligator, eds., *Handbook of Econometrics, Volume 3*, Amsterdam: North Holland, 1986, pp. 1465–1514.

Hornbeck, Richard, "The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe," *American Economic Review*, 2012, *102* (4), 1477–1507.

Hsiang, Solomon M. and Amir S. Jina, "The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones," Working Paper 20352, National Bureau of Economic Research July 2014.

_ and Marshall Burke, "Climate, Conflict, and Social Stability: What Does the Evidence Say?," *Climatic Change*, 2014, *123* (1), 39–55.

_ , _ , and Edward Miguel, "Quantifying the Influence of Climate on Human Conflict," *Science*, 2013, *341* (151), 1212–1228.

Iyigun, Murat, "Luther and Suleyman," *Quarterly Journal of Economics*, November 2008, *123* (4), 1465–1494.

_ , Nathan Nunn, and Nancy Qian, "The Long-run Effects of Agricultural Productivity and Conflict: Evidence from Potatoes, 1400–1900," Yale University Working Papers, Yale University 2016.

Jia, Ruixue, "Weather Shocks, Sweet Potatoes and Peasant Revolts in Historical China," *Economic Journal*, 2014, *124*, 92–118.

Klepper, Steven and Edward E. Leamer, "Consistent Sets of Estimates for Regressions with Errors in all Variables," *Econometrica*, 1984, *52* (1), 163–184.

Kung, James Kai-sing and Chicheng Ma, "Can Cultural Norms Reduce Conflicts? Confucianism and Peasant Rebellions in Qing China," *Journal of Development Economics*, 2014, *111*, 132–149.

Lamb, H.H., *Climate, History and the Modern World* Climate, History and the Modern World, New York: Routledge, 1995.

Lee, Harry F., David D. Zhang, Peter Brecke, and Jie Fei, "Positive correlation between the North Atlantic Oscillation and violent conflicts in Europe," *Climate Research*, 2013, *56* (1), 1–10.

Levy, Jack S., *War in the Modern Great Power System, 1495–1975*, Lexington, KY: University of Kentucky Press, 1983.

Ludlow, Francis and Solomon Hsiang, "No adaptation to climate during one millennium of Irish history," University of Berkeley at California Working Paper April 2016.

Luterbacher, Jurg, Daniel Dietrich, Elena Xoplaki, Martin Grosjean, and Heinz Wanner, "European Seasonal and Annual Temperature Variability, Trends, and Extremes Since 1500," *Science*, 2004, *303* (5663), 1499–1503.

Mann, Michael E., "Little Ice Age," in Micahel C. MacCraken and John S. Perry, eds., *Encyclopedia of Global Environmental Change. Volume 1. The Earth System: Physical and Chemical Dimensions of Global Environmental Change*, Chichester: John Wiley & Sons Ltd, 2002, pp. 504–509.

_ , Zhihua Zhang, Scott Rutherford, Raymond S. Bradley, Malcolm K. Hughes, Drew Shindell, Caspar Ammann, Greg Faluvegi, and Fenbiao Ni, "Global Signatures and Dynamical Origins of the Little Ice Age and Medieval Climate Anomaly," *Science*, 2009, *326*, 1256–1260.

_ , _ , _ , _ , _ , _ , _ , _ , and _ , "Supporting Online Material for: Global Signatures and Dynamical Origins of the Little Ice Age and Medieval Climate Anomaly," 2009. Online Appendix.

Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw, "The Impact of Global Warming on Agriculture: A Ricardian Analysis," *The American Economic Review*, 1994, *84* (4), 753–771.

Miguel, Edward, Shanker Satyanath, and Ernest Sergenti, "Economic Shocks and Civil Conflict: An Instrumental Variables Approach," *Journal of Political Economy*, August 2004, *112* (4), 725–753.

Nordhaus, William D., "Reflections on the Economics of Climate Change," *Journal of Economic Perspectives*, 1993, *7* (4), 11–25.

Nunn, Nathan and Nancy Qian, "The Columbian Exchange: A History of Disease, Food and Ideas," *Journal of Economic Perspectives*, 2010, *24* (2), 163–188.

_ and _ , "The Potato's Contribution to Population and Urbanization: Evidence from a Historical Experiment," *Quarterly Journal of Economics*, 2011, *126* (2), 593–650.

Oster, Emily, "Witchcraft, Weather and Economic Growth in Renaissance Europe," *Journal of Economic Perspectives*, 2004, *18* (1), 215–228.

Parker, Geoffrey, *Global Crisis: War, Climate Change and Catastrophe in the Seventeenth Century*, Yale University Press, 2013.

Pauling, Andreas, Jurg Luterbacher, Carlo Casty, and Heinz Wanner, "Five Hundred Years of Gridded High-Resolution Precipitation Reconstructions over Europe and the Connection to Large-Scale Circulation," *Climate Dynamics*, 2006, *26*, 387–405.

Schlenker, Wolfram and Michael J. Roberts, "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proceedings of the National Academy of Sciences*, 2009, *106* (37), 15594–15598.

Shaw, Stanford J., *History of the Ottoman Empire and Modern Turkey. Volume 1. Empire of the Gazis: The Rise and Decline of the Ottoman Empire, 1280–1808*, Cambridge: Cambridge University Press, 1976.

Tol, Richard S.J. and Sebastian Wagner, "Climate Change and Violent Conflict in Europe over the Last Millennium," *Climate Change*, 2010, *99*, 65–79.

Waldinger, Maria, "The Economic Effects of Long-Term Climate Change: Evidence from the Little Ice Age," 2015. Working Paper, London School of Economics.

White, Sam, *The Climate of Rebellion in the Early Modern Ottoman Empire*, New York: Cambridge University Press, 2011.

Wimmer, Andreas and Brian Min, "From Empire to Nation-State: Explaining Wars in the Modern World, 1816–2001," *American Sociological Review*, 2006, *71* (6), 867–897.

Zhang, David D., C.Y. Jim, George C-S Lin, Yuan-Qing He, James J. Wang, and Harry F. Lee, "Climate Change, Wars and Dynastic Cycles in China over the Last Millennium," *Climate Change*, 2006, *76* (3), 459–477.

_ **, Peter Brecke, Harry F. Lee, , Yuan-Qing, and Jane Zhang**, "Global Climate Change, War, and Population Decline in Recent Human History," *Proceedings of the National Academy of Sciences*, 2007, *104* (49), 19214–19219.

A Appendix (Not for Publication)

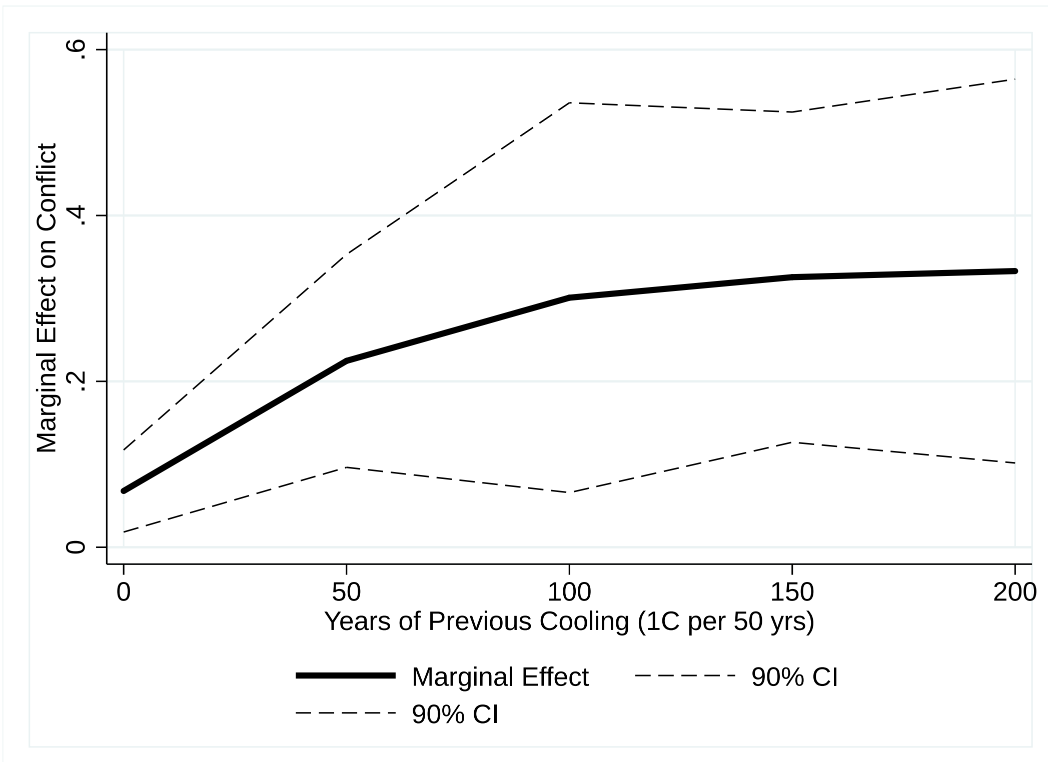
We use two sources of data to construct our baseline conflict database: Brecke's *Conflict Catalogue* and Clodfelter's (2008) *Warfare and Armed Conflicts*. Using the information on the names of the locations of battles from our sources, we then manually geo-referenced and digitized the location. In our analysis the unit of observation is a grid-cell and a time period. In the underlying raw data we identify a battle, defined as a conflict recorded in our sources, occurring in a location and in a calendar year. We code conflicts that are part of the same war, but occurring in different locations or different years as separate battles. For our analysis, we thus aggregate all battles occurring in a grid-cell and over a time period to obtain a measure of the total number of battles in that grid-cell and time period.

To measure cooling we use temperature data estimates constructed by Mann et al. (2009a). The original data set includes gridded average temperature (0.5 degree by 0.5 degree grid-cells) annually from 500 to 1900 and covering the entire globe. Mann et al. (2009a) use a climate field reconstruction approach to reconstruct global patterns of surface temperature for a long historical period. The construction uses proxy data with global coverage that comprises 1,036 tree ring series, 32 ice core series, 15 marine coral series, 19 documentary series, 14 speleothem series, 19 lacustrine sediment series, and 3 marine sediment series (Mann et al., 2009b).

Following Nunn and Qian (2011), we construct measures of suitability using the *FAO*'s Global Agro-Ecological Zones (*GAEZ*) data base. We differ in using a more recent version than was unavailable to Nunn and Qian (2011). The data include information on 154 different crops and the physical environment of 2.2 million cells spanning the whole world, with each cell covering an area of 5 arc minutes by 5 arc minutes, or roughly 10km by 10km cells. Using nine climate characteristics of each cell, such as frequency of wet days, precipitation, mean temperature, etc., *FAO* calculated an estimate of the potential yield of each crop in each cell, given an assumed level of crop management and input use. With some additional data processing, the *FAO* then calculated the constraint-free crop yields and referenced the potential yield of each cell as a percent of this benchmark. The index ranges from 0 to 100. The *GAEZ* cells are 10km by 10km and finer than the cells used in our analysis. Thus, we measure suitability at the cell level as the average suitability measure of land within the cell.

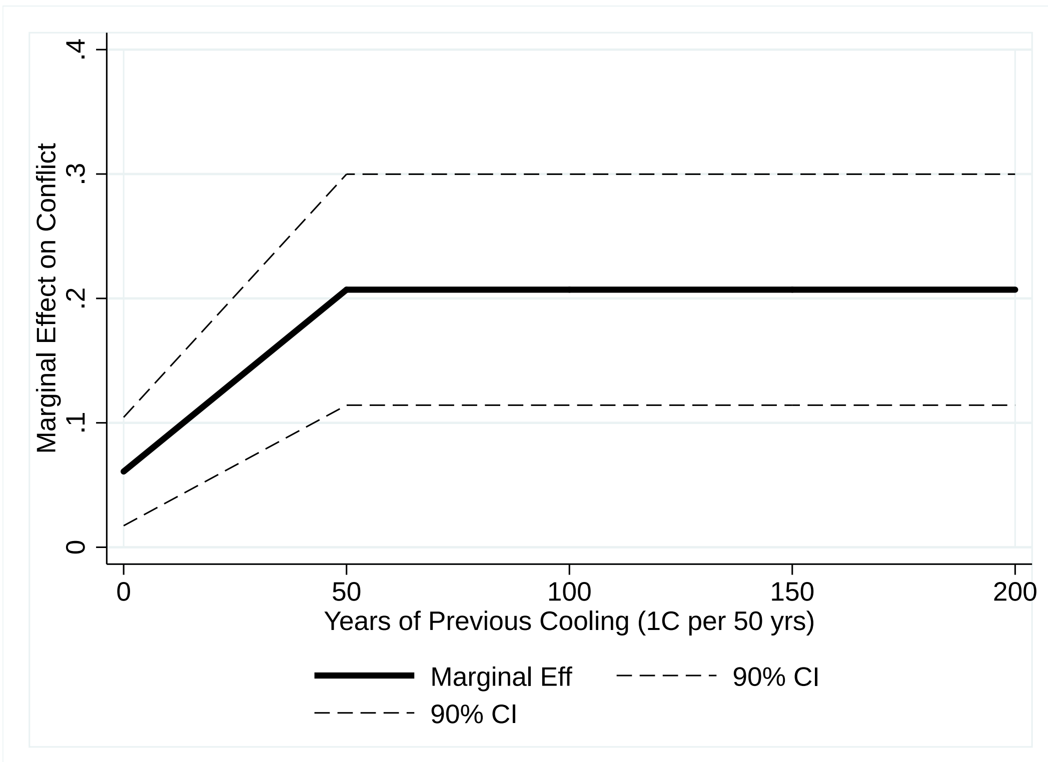
It is important to note that in calculating suitability, the FAO's agro-climatic model explicitly avoids taking into account factors that are easily manipulated by human intervention. For example, the fact that Europe has been significantly de-forested over time does not affect the suitability measure because the amount of forests does not factor into suitability. Instead, the model focuses on agricultural inputs that are difficult to manipulate such as climate and the average hours of sunshine in each season. Similarly, the GAEZ model allows us to choose inputs for factors such as mechanization and irrigation. To the best of our ability, we choose inputs to approximate for the level of technology available during our historical period of study (e.g., rain-fed and low input intensity).

Figure A.1: How the Marginal Effect of Cooling on Conflict Change Varies Depending on Previous Periods of Cooling: Robustness to the use of 800km by 800km grid-cells.



Notes: The *y*-axis reports the marginal effects of cooling on conflict change in the current time period. The *x*-axis reports the number of previous years of cooling at one degree celsius per fifty-year period. The predicted effects are based on coefficients from equation (5). The coefficients and standard errors are available upon request.

Figure A.2: How the Marginal Effect of Cooling on Conflict Change Varies Depending on Previous Periods of Cooling: LASSO Estimates



Notes: The y-axis reports the marginal effects of cooling on conflict change in the current time period. The x-axis reports the number of previous years of cooling at one degree celsius per fifty-year period. The predicted effects are based on coefficients from the LASSO model. The coefficients and standard errors are available upon request.

Table A.1: The Effect of Cooling on Conflict: Robustness to the Exclusion of the Twenty Five Largest Wars

		Dependent Variable: Fifty-Year Change in Conflict Incidence, $\Delta y_{i,d-5}$									
	Size of Omitted War (Number of Conflicts)	$\Delta C_{i,d-5}$		$\Delta C_{i,d-10}$		$\Delta C_{i,d-5}$ x $\Delta C_{i,d-10}$				Marginal Effect of Cooling	
		Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Obs.	R-sq.	100 years	Std. Err.
(1)	No Omission	0.00344	(0.0130)	0.0874**	(0.0386)	0.0436***	(0.0146)	11,480	0.017	0.131	(0.041)
(2)	74	0.00382	(0.0131)	0.0894**	(0.0388)	0.0463***	(0.0148)	11,480	0.016	0.136	(0.042)
(3)	70	0.000485	(0.0131)	0.0907**	(0.0389)	0.0438***	(0.0145)	11,480	0.021	0.135	(0.042)
(4)	66	0.00279	(0.0132)	0.0741*	(0.0381)	0.0435***	(0.0146)	11,480	0.016	0.118	(0.041)
(5)	63	0.00315	(0.0130)	0.0890**	(0.0387)	0.0432***	(0.0147)	11,480	0.016	0.132	(0.041)
(6)	55	0.00285	(0.0130)	0.0845**	(0.0384)	0.0448***	(0.0146)	11,480	0.016	0.129	(0.041)
(7)	48	0.00107	(0.0131)	0.0909**	(0.0390)	0.0414***	(0.0147)	11,480	0.017	0.132	(0.041)
(8)	43	-0.00800	(0.0120)	0.0721*	(0.0370)	0.0413***	(0.0145)	11,480	0.016	0.113	(0.040)
(9)	42	0.00250	(0.0131)	0.0901**	(0.0388)	0.0417***	(0.0146)	11,480	0.016	0.132	(0.041)
(10)	35	0.00119	(0.0132)	0.0891**	(0.0387)	0.0431***	(0.0146)	11,480	0.019	0.132	(0.041)
(11)	32	0.00143	(0.0130)	0.0955**	(0.0389)	0.0403***	(0.0145)	11,480	0.016	0.136	(0.042)
(12)	31	0.000596	(0.0130)	0.0810**	(0.0371)	0.0446***	(0.0148)	11,480	0.018	0.126	(0.040)
(13)	31	0.00344	(0.0130)	0.0874**	(0.0386)	0.0436***	(0.0146)	11,480	0.017	0.131	(0.041)
(14)	28	0.00339	(0.0130)	0.0930**	(0.0391)	0.0445***	(0.0146)	11,480	0.017	0.138	(0.042)
(15)	27	0.00576	(0.0130)	0.0937**	(0.0386)	0.0411***	(0.0146)	11,480	0.016	0.135	(0.041)
(16)	24	0.00264	(0.0131)	0.0860**	(0.0386)	0.0435***	(0.0146)	11,480	0.017	0.129	(0.041)
(17)	23	0.00252	(0.0131)	0.0871**	(0.0386)	0.0431***	(0.0147)	11,480	0.017	0.130	(0.041)
(18)	23	0.00227	(0.0131)	0.0837**	(0.0384)	0.0423***	(0.0147)	11,480	0.017	0.126	(0.041)
(19)	23	0.00323	(0.0130)	0.0892**	(0.0388)	0.0434***	(0.0146)	11,480	0.017	0.133	(0.041)
(20)	22	0.00395	(0.0130)	0.0884**	(0.0386)	0.0435***	(0.0146)	11,480	0.017	0.132	(0.041)
(21)	20	0.00197	(0.0129)	0.0933**	(0.0385)	0.0407***	(0.0146)	11,480	0.016	0.134	(0.041)
(22)	19	0.00187	(0.0128)	0.0856**	(0.0384)	0.0440***	(0.0146)	11,480	0.017	0.130	(0.041)
(23)	19	0.00474	(0.0130)	0.0817**	(0.0368)	0.0433***	(0.0144)	11,480	0.017	0.125	(0.039)
(24)	19	0.00370	(0.0130)	0.0840**	(0.0384)	0.0428***	(0.0146)	11,480	0.017	0.127	(0.041)
(25)	18	0.00352	(0.0130)	0.0860**	(0.0385)	0.0429***	(0.0145)	11,480	0.017	0.129	(0.041)
(26)	18	0.00339	(0.0130)	0.0874**	(0.0386)	0.0435***	(0.0147)	11,480	0.017	0.131	(0.041)

Notes: The regression controls for cell and time fixed effects. Observations are at the decade and 400km by 400km grid-cell level. Standard errors are clustered at the cell level. Each row is estimated with a sample where all battles from a given war are omitted. This does not affect the number of observations since the sample includes observations with zero conflicts.

Table A.2: The Very Long-Run Effect of Cooling on Conflict using the Fully Flexible Specification

	Dependent Variable: Fifty-Year Change in Conflict Incidence, $\Delta y_{i,d-5}$			
	(1)	(2)	(3)	(4)
Cooling:				
$\Delta C_{i,d-5} \times \Delta C_{i,d-10}$	0.0874**	0.0858**	0.114**	0.159***
	(0.0386)	(0.0407)	(0.0487)	(0.0603)
$\Delta C_{i,d-5}$	0.0436***	0.0516***	0.0330*	0.0721**
	(0.0146)	(0.0180)	(0.0194)	(0.0279)
$\Delta C_{i,d-10}$	0.00344	0.00391	0.0138	0.0645***
	(0.0130)	(0.0137)	(0.0198)	(0.0240)
$\Delta C_{i,d-5} \times \Delta C_{i,d-15}$		-0.0106	-0.0357	0.0451
		(0.0500)	(0.0570)	(0.0784)
$\Delta C_{i,d-10} \times \Delta C_{i,d-15}$		0.00925	-0.0150	0.0103
		(0.0408)	(0.0455)	(0.0511)
$\Delta C_{i,d-15}$		-0.000634	-0.00354	0.0325
		(0.0180)	(0.0180)	(0.0209)
$\Delta C_{i,d-5} \times \Delta C_{i,d-20}$			0.0634	0.0825
			(0.0494)	(0.0702)
$\Delta C_{i,d-10} \times \Delta C_{i,d-20}$			0.106**	0.160***
			(0.0473)	(0.0543)
$\Delta C_{i,d-15} \times \Delta C_{i,d-20}$			-0.00878	0.0385
			(0.0461)	(0.0581)
$\Delta C_{i,d-20}$			-0.0465**	-0.0238
			(0.0188)	(0.0190)
$\Delta C_{i,d-5} \times \Delta C_{i,d-25}$				0.0223
				(0.0403)
$\Delta C_{i,d-10} \times \Delta C_{i,d-25}$				0.00836
				(0.0805)
$\Delta C_{i,d-15} \times \Delta C_{i,d-25}$				-0.0189
				(0.0666)
$\Delta C_{i,d-20} \times \Delta C_{i,d-25}$				0.0243
				(0.0685)
$\Delta C_{i,d-25}$				0.0566**
				(0.0220)
Observations	11,480	10,080	8,680	7,280
R-squared	0.017	0.019	0.022	0.030
Marginal effect of cooling with 1C of cooling in each previous 50-year period:				
50 Years of Prev. Cooling	0.131	0.137	0.147	0.231
	(0.041)	(0.043)	(0.050)	(0.066)
100 Years of Prev. Cooling		0.131	0.125	0.341
		(0.065)	(0.085)	(0.124)
150 Years of Prev. Cooling			0.174	0.359
			(0.072)	(0.109)
200 Years of Prev. Cooling				0.381
				(0.129)

Notes: All regressions control for cell and time fixed effects. Observations are at the decade and 400km by 400km grid-cell level. Standard errors, clustered at the grid-cell level, are reported in parentheses.

Table A.3: The Very Long-Run Effect of Cooling on Conflict using the Fully Flexible Specification: Robustness to Controls

	Dependent Variable: Fifty-Year Change in Conflict Incidence, $\Delta y_{i,d-5}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	Conflict Incidence 1401-1450 x Time FE	Number of Conflicts 1401-1450 x Time FE	Temperature 1401-1450 x Time FE	Suitability for Old World Staples x Time FE, Potatoes x post-1700	Number of Cities in 1400 x Time FE	Geographic Controls x Time FE	Level of Temperature, $T_{i,d}$
Cooling:								
$\Delta C_{i,d-5} \times \Delta C_{i,d-10}$	0.159***	0.143**	0.147**	0.173***	0.109*	0.155***	0.223***	0.159***
	(0.0603)	(0.0599)	(0.0594)	(0.0640)	(0.0590)	(0.0591)	(0.0823)	(0.0599)
$\Delta C_{i,d-5} \times \Delta C_{i,d-15}$	0.0451	0.0303	0.0408	0.0661	-0.00570	0.0557	0.106	0.0415
	(0.0784)	(0.0774)	(0.0775)	(0.0890)	(0.0821)	(0.0770)	(0.118)	(0.0788)
$\Delta C_{i,d-5} \times \Delta C_{i,d-20}$	0.0825	0.104	0.0892	0.0454	0.138*	0.0764	0.0610	0.0931
	(0.0702)	(0.0690)	(0.0682)	(0.0784)	(0.0722)	(0.0689)	(0.101)	(0.0711)
$\Delta C_{i,d-5} \times \Delta C_{i,d-25}$	0.0223	0.0428	0.0425	0.0131	0.0463	0.0335	-0.0293	0.0150
	(0.0403)	(0.0390)	(0.0399)	(0.0449)	(0.0406)	(0.0396)	(0.0554)	(0.0403)
$\Delta C_{i,d-10} \times \Delta C_{i,d-15}$	0.0103	0.0120	0.0264	0.0104	0.0297	0.0208	0.0501	0.00359
	(0.0511)	(0.0490)	(0.0500)	(0.0540)	(0.0492)	(0.0513)	(0.0801)	(0.0512)
$\Delta C_{i,d-10} \times \Delta C_{i,d-20}$	0.160***	0.126**	0.139***	0.142**	0.107*	0.155***	0.180**	0.166***
	(0.0543)	(0.0535)	(0.0529)	(0.0643)	(0.0565)	(0.0529)	(0.0808)	(0.0539)
$\Delta C_{i,d-10} \times \Delta C_{i,d-25}$	0.00836	0.0120	-0.000408	-0.00482	0.0398	0.0180	-0.0224	0.00460
	(0.0805)	(0.0793)	(0.0791)	(0.0897)	(0.0837)	(0.0795)	(0.120)	(0.0808)
$\Delta C_{i,d-15} \times \Delta C_{i,d-20}$	0.0385	0.0285	0.0376	0.0191	0.0370	0.0391	0.119	0.0388
	(0.0581)	(0.0553)	(0.0562)	(0.0589)	(0.0548)	(0.0569)	(0.0896)	(0.0583)
$\Delta C_{i,d-15} \times \Delta C_{i,d-25}$	-0.0189	-0.0112	-0.00936	-0.0363	-0.0232	-0.00755	0.0715	-0.0237
	(0.0666)	(0.0641)	(0.0643)	(0.0731)	(0.0719)	(0.0667)	(0.100)	(0.0670)
$\Delta C_{i,d-20} \times \Delta C_{i,d-25}$	0.0243	-0.0308	-0.0202	0.0813	-0.0192	-0.00739	-0.0211	0.0265
	(0.0685)	(0.0640)	(0.0652)	(0.0749)	(0.0660)	(0.0673)	(0.0916)	(0.0687)
$\Delta C_{i,d-5}$	0.0721**	0.0674**	0.0664**	0.0830**	0.0571*	0.0670**	0.150***	0.0509*
	(0.0279)	(0.0279)	(0.0280)	(0.0368)	(0.0324)	(0.0281)	(0.0430)	(0.0282)
$\Delta C_{i,d-10}$	0.0645***	0.0604**	0.0650***	0.0508	0.0388	0.0634***	0.0395	0.0602**
	(0.0240)	(0.0243)	(0.0239)	(0.0354)	(0.0245)	(0.0237)	(0.0453)	(0.0247)
$\Delta C_{i,d-15}$	0.0325	0.0291	0.0339	0.0491	0.0490*	0.0306	0.0223	0.0283
	(0.0209)	(0.0209)	(0.0207)	(0.0322)	(0.0250)	(0.0210)	(0.0391)	(0.0212)
$\Delta C_{i,d-20}$	-0.0238	-0.0224	-0.0239	-0.0601	-0.0387	-0.0240	-0.0109	-0.0208
	(0.0190)	(0.0186)	(0.0188)	(0.0386)	(0.0237)	(0.0190)	(0.0388)	(0.0195)
$\Delta C_{i,d-25}$	0.0566**	0.0511**	0.0512**	0.101***	0.0679***	0.0523**	-0.0210	0.0570**
	(0.0220)	(0.0214)	(0.0214)	(0.0381)	(0.0256)	(0.0216)	(0.0428)	(0.0220)
Observations	7,280	7,280	7,280	7,280	6,994	7,280	7,280	7,280
R-squared	0.030	0.061	0.060	0.032	0.048	0.047	0.058	0.030
Marginal effect of cooling with 1C of cooling in each previous 50-year period:								
50 Years of Prev. Cooling	0.231	0.211	0.214	0.256	0.166	0.222	0.374	0.210
	(0.066)	(0.065)	(0.064)	(0.074)	(0.067)	(0.064)	(0.088)	(0.066)
100 Years of Prev. Cooling	0.276	0.241	0.255	0.322	0.160	0.278	0.480	0.251
	(0.110)	(0.109)	(0.109)	(0.123)	(0.112)	(0.110)	(0.168)	(0.111)
150 Years of Prev. Cooling	0.359	0.345	0.344	0.368	0.299	0.355	0.541	0.345
	(0.109)	(0.105)	(0.105)	(0.119)	(0.109)	(0.108)	(0.170)	(0.108)
200 Years of Prev. Cooling	0.381	0.388	0.387	0.381	0.345	0.388	0.511	0.359
	(0.129)	(0.128)	(0.127)	(0.143)	(0.129)	(0.129)	(0.193)	(0.129)

Notes: The regression controls for cell and time fixed effects. Geographic controls (column 7) include latitude, longitude, elevation, slope and the distance to the nearest coast. Observations are at the decade and 400km by 400km grid-cell level. Standard errors, clustered at the grid-cell level, are reported in parentheses. The robustness specifications in columns 2-7 are the same as columns 2-7 of Table 3. Column 8 is the same as column 7 of Table 1.

Table A.4: The Very Long-Run Effect of Cooling on Conflict using the Fully Flexible Specification: Alternative Measures of Conflict

	Dependent Variable: Fifty-Year Change in Conflict Measure		
	(1)	(2)	(3)
	Conflict Incidence (Baseline)	Total Number of Conflicts	Natural Log of Total Number of Conflicts
Cooling:			
$\Delta C_{i,d-5}$ x $\Delta C_{i,d-10}$	0.159***	0.586**	0.503***
	(0.0603)	(0.237)	(0.175)
$\Delta C_{i,d-5}$ x $\Delta C_{i,d-15}$	0.0451	0.149	0.127
	(0.0784)	(0.232)	(0.218)
$\Delta C_{i,d-5}$ x $\Delta C_{i,d-20}$	0.0825	0.578***	0.358*
	(0.0702)	(0.219)	(0.186)
$\Delta C_{i,d-5}$ x $\Delta C_{i,d-25}$	0.0223	0.106	0.0916
	(0.0403)	(0.127)	(0.110)
$\Delta C_{i,d-10}$ x $\Delta C_{i,d-15}$	0.0103	0.197	0.0749
	(0.0511)	(0.162)	(0.143)
$\Delta C_{i,d-10}$ x $\Delta C_{i,d-20}$	0.160***	0.681***	0.564***
	(0.0543)	(0.173)	(0.163)
$\Delta C_{i,d-10}$ x $\Delta C_{i,d-25}$	0.00836	0.129	0.0572
	(0.0805)	(0.195)	(0.225)
$\Delta C_{i,d-15}$ x $\Delta C_{i,d-20}$	0.0385	0.503**	0.185
	(0.0581)	(0.254)	(0.177)
$\Delta C_{i,d-15}$ x $\Delta C_{i,d-25}$	-0.0189	-0.0240	-0.0478
	(0.0666)	(0.245)	(0.187)
$\Delta C_{i,d-20}$ x $\Delta C_{i,d-25}$	0.0243	0.593**	0.199
	(0.0685)	(0.257)	(0.189)
$\Delta C_{i,d-5}$	0.0721**	0.0587	0.200**
	(0.0279)	(0.0958)	(0.0805)
$\Delta C_{i,d-10}$	0.0645***	0.166**	0.192***
	(0.0240)	(0.0805)	(0.0678)
$\Delta C_{i,d-15}$	0.0325	0.198**	0.125**
	(0.0209)	(0.0775)	(0.0568)
$\Delta C_{i,d-20}$	-0.0238	-0.00904	-0.0609
	(0.0190)	(0.0568)	(0.0537)
$\Delta C_{i,d-25}$	0.0566**	0.0676	0.146**
	(0.0220)	(0.0740)	(0.0627)
Observations	7,280	7,280	7,280
R-squared	0.030	0.027	0.034
Predicted marginal effects of (1C of cooling per 50 years) for:			
50 Years of Prev. Cooling	0.231	0.644	0.703
	(0.066)	(0.219)	(0.193)
100 Years of Prev. Cooling	0.276	0.794	0.830
	(0.110)	(0.326)	(0.317)
150 Years of Prev. Cooling	0.359	1.372	1.188
	(0.109)	(0.383)	(0.321)
200 Years of Prev. Cooling	0.381	1.478	1.280
	(0.129)	(0.425)	(0.376)

Notes: The regression controls for cell and time fixed effects. Observations are at the decade and 400km by 400km grid-cell level. Standard errors, clustered at the grid-cell level, are reported in parentheses.