INVESTIGATING THE HETEROGENEOUS EFFECTS OF TEMPERATURE ON ECONOMIC GROWTH

BY

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THESIS

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Abstract

This paper investigates the effect of temperature on economic growth on a panel of 156 countries over a 50-year time period. We use random fluctuations in a country's annual average temperature over time as our strategy for identifying the causal effect of temperature on GDP per capita growth. Previous work has found that temperature has a statistically significant relationship with growth when fitting data from all countries with a nonlinear model. We hypothesize that countries with different observable characteristics have differing responses to changes in temperature and we use recursive model partitioning to find data-driven splits in the dataset. We run the model on a number of country-level characteristics and we find that GDP per capita percentile and historical mean temperature are the variables that best fit the data. We divide the countries into four groups: low income - low temperature (20 countries), low income - high temperature (70 countries), high income - low temperature (36 countries), high income - high temperature (33 countries). We obtain different coefficients for the relationship between temperature and growth for each group. We also use agricultural GDP per capita growth as a dependent variable and obtain coefficients for the relationship between temperature and agricultural GDP per capita growth. We compare our results with results obtained from a model that does not have any splits (Burke et al., 2015). We find that dividing countries into groups using a data-driven method has a significant impact on future projections of GDP per capita growth under different climate change scenarios and how we interpret the effects that changes in average temperatures might have on countries. A model that does not split countries into groups overestimates the gains that low temperature countries might make from rising temperatures and underestimates the ability of high income - high temperature countries to capitalize on the high temperatures that they regularly experience. Our model takes into account adaptations to historical temperatures that countries may have and we find that low temperature countries have lower "optimum temperatures" that help them achieve maximum growth and likewise, high temperature countries have higher "optimum temperatures." We predict that low income - low temperature countries and high income - low temperature countries are likely to face low growth (1.73 % and 0.00879 % respectively) in the year 2100; low income - high temperature countries will face negative growth (-3.19 %) and high income - high temperature countries will face positive growth (3.16 %).

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Chapter 1

Introduction and Motivation

Climate is "the joint probability distribution over several weather parameters, such as temperature or wind speed, that can be expected to occur at a given location during a specific interval of time" (Carleton and Hsiang, 2016). The scientific community's consensus is that "differences in vulnerability and exposure arise from non-climactic factors and from multidimensional inequalities often produced by uneven development processes" (IPCC, 2014b). Adding to our understanding of how the economy is likely to change as a response to projected changes in climate remains an important research objective. The Intergovernmental Panel on Climate Change (IPCC) have stated that "human influence on climate is clear, and recent anthropogenic emissions of greenhouse gases are the highest in history. Recent climate changes have had widespread impact on human and natural systems" (IPCC, 2014b). In our paper, we add to the body of work that explores how climate affects human actions (i.e. the economy) and in turn, how that might change the human actions that affect the climate. In this paper, we employ some of the "machine learning" techniques that have arisen in recent years to help us in our understanding of the complex relationship between climate and the economy (Athey and Imbens, 2015; Zeileis et al., 2008).

Dell et al. (2012) use historical fluctuations in temperature as a strategy for identifying the causal impact of temperature on economic growth. Dell et al. (2012) find that there are "large and negative impacts of higher temperatures on growth, but only in poor countries" and for high income countries, "changes in temperature do not have a robust discernable effect on growth." We find that both high and low income countries face negative impacts of higher temperatures, depending on the mean temperatures they experience historically. Dell et al. (2012) note that their analysis only accounts for short-run economic impacts of temperature in the economy and that countries may adapt to a particular temperature in the long run. Our paper seeks to test for the presence of this adaptation to historical climate.

Burke et al. (2015) use historical fluctuations in temperature as their identification strategy and account for nonlinearity in the relationship between temperature and growth. Burke et al. (2015) find that productivity peaks "at an annual average temperature of 13 °C and [declines] strongly at higher temperatures." Burke et al. (2015) obtain their results by fitting data from all countries in their dataset using one model. We hypothesize that countries with different observable characteristics respond differently to temperature fluctuations and explore this heterogeneity with a data-driven algorithm. In particular, we use a number of "partitioning variables" (GDP per capita percentile, Historical mean temperature, agricultural share of GDP, etc.) and find a value within each variable that optimally divides the data into subgroups. For instance, with mean temperature, we arrange the dataset according to the partitioning variable from the lowest value (-3.97 °C) to the highest value (28.37 °C) and run regressions for subgroups of the data at 0.5 °C intervals. For each value of the partitioning variable c , the dataset is split into two subgroups: observations $< c$ and observations $\geq c$. We run a regression that fits our model to each subgroup and calculate the residual sum of squares (RSS) for each regression. The "optimal" value of c is the one where the total RSS for both regressions is minimized. We then compare optimal values across partitioning variables to determine which variable is best suited for splitting the data into subgroups, again finding the value of c across variables that corresponds to the lowest total RSS. (Table 3.2 - 3.4)

The first optimal split occurs at the 54th percentile for GDP per capita. We divide the dataset into two groups: High Income (GDP Percentile $\geq$ 54) and Low Income (GDP Percentile $<$ 54). We then run the test on High Income and Low Income groups separately, imposing a minimum node size constraint where we ensure that there are at least 10 countries in each group. For the High Income group, the second optimal split occurs where historical mean temperature is 13 °C and for the Low Income group the second optimal split occurs where the historical mean temperature is 17 °C. Hence, the whole dataset is divided into four groups in total: low income - low temperature, low income - high temperature, high income - low temperature and high income - high temperature. We provide descriptive statistics for the subgroups in Table 3.5.

Under Burke et al. (2015)'s model, temperature has a statistically significant impact on economic growth for all countries. In our paper, we find that the statistical significance of the relationship between temperature and growth is largely driven by high income countries (Table 4.1) and in particular, high income - low temperature countries. We find that the predictions for average global GDP growth do not change much when you account for splitting the data but the average GDP growth in each subgroup does vary significantly (Table 4.2; Table 4.3).

We generate predictions for GDP per capita growth using our model under four different climate scenarios: baseline temperatures (1960 - 2010), global average temperature increase of 1 °C, global average temperature increase of 2 °C and RCP 8.5 temperature projections for the year 2100 (Riahi et al., 2011). We compare our predictions for GDP per capita growth for each scenario against the global average generated by Burke et al. (2015)'s model (BHM) (Table 4.2; Table 4.3). We also compare predictions for each group generated under BHM and under our model (Het) (Table 4.4; Table 4.5).

In general, our results support the view that there is long-run adaptation to climate at the country-level. If there is no adaptation to mean temperatures over time and we assume that there is a "hill-shaped relationship" (Mendelsohn and Dinar, 1999) between temperature and economic growth, we will see that high temperature countries will face high damages when mean temperatures increase, because they are on the negatively sloped side of the 'hill.' Low temperature countries will have increased growth as they approach the optimal temperature for growth and growth will decline if mean temperatures increase beyond the optimal temperature for growth. If there is adaptation to mean temperatures over time, we expect that low temperature countries will have a lower optimal temperature for growth and high temperature countries will have a higher optimal temperature for growth. With adaptation, low temperature countries may face damages as a result of increased mean temperatures because they are beyond the low temperature optimum, even if they are moving towards the ‘global optimum’ temperature for growth. Similarly, high temperature countries may not have damages as high as we would predict because they might be moving towards the high temperature optimum, even as they are moving away from the ‘global optimum’ temperature for growth. BHM generates a global optimum temperature for growth of 13 °C, and our results show that there is a lower optimal temperature at 9 °C and a higher optimal temperature at 17 °C (Figures 4.4 - 4.5). We use a detailed comparison of predicted values generated under BHM’s model and our model to show that our view of the magnitude and severity of climate change damages will differ depending on whether or not there is adaptation to climate in the long run (Tables 4.5 - 4.6).

For the RCP 8.5 scenario, BHM predicts that low income - low temperature countries will have relatively high growth (4.83 %) whereas our model predicts that they will have low growth (1.73 %). For low income - high temperature countries, both models predict that they will have negative growth in the year 2100, though our model (-3.19 %) predicts slightly larger damages than BHM (-2.79 %). For the high income - low temperature countries, BHM predicts high growth (2.02 %) whereas our model predicts low growth (0.00879 %). For high income - high temperature countries, BHM predicts negative growth (-0.0988 %) whereas our model predicts high growth (3.16 %). Finally, we also generate predictions comparing total GDP per capita growth and agricultural GDP per capita growth between the different groups (Table 4.8; Table 4.9) and we discuss those results in more detail in Chapter 4.

Our findings suggest that because countries respond differently to changes in temperature, it may be very difficult to come to a global consensus on climate change. However, our findings also suggest that, if climate change is not mitigated, temperature change will lead to substantial damages in both rich and poor countries.

Chapter 2

Background

2.1 Climate Change

The Intergovernmental Panel on Climate Change defines "climate change" as "a change in the state of the climate that can be identified (e.g. by using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer." (IPCC, 2014b) Figure 2.1 below shows us that average surface temperature has been increasing since 1850 and that there is "robust multi-decadal warming."(IPCC, 2013) Though discussion on the interaction between cli-

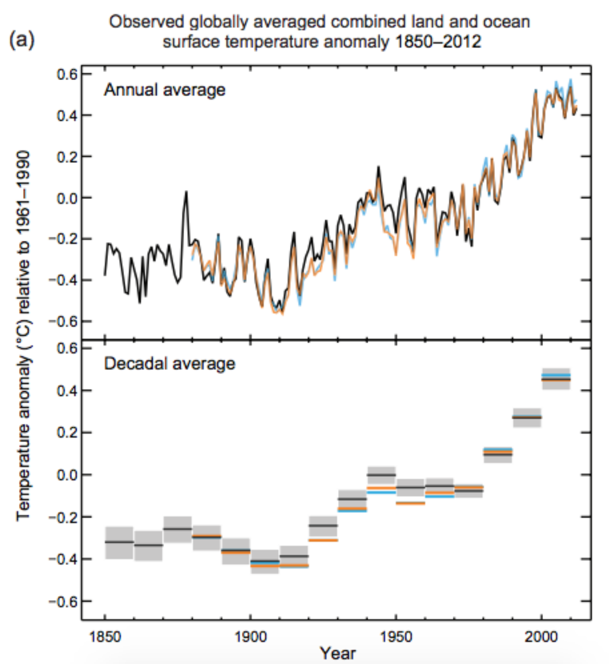

Figure 2.1
Global Average Surface Temperature 1850 – 2012,
Figure SPM1a, (IPCC, 2013).

mate and the economy have gained much ardor and traction in recent years, thinkers throughout history have grappled with the impact of climate on human activities. In the *Muqaddimah*, Ibn Khaldŭn outlines his theory of how climate affects human civilization. Ibn Khaldŭn describes how people living in "temperate" regions experience "temperate" conditions and this is reflected in "their dwellings, clothings, foodstuffs and crafts," whereas those who were exposed to more extreme temperatures near the equator or near the poles tended to have less "developed" economies. Climate also affects human capital: "The physique and character of its inhabitants are temperate to the (high) degree necessitated by the composition of the air [climate] in which they live." (Khaldŭn, 1958) In 1748, Montesquieu wrote in his *The Spirit of Law* regarding how men changed their behavior when exposed to a hotter climate: "If we reflect on the late wars, [...] we shall find that the northern people, transplanted into southern regions, did not perform such exploits as their countrymen who, fighting in their own climate, possessed their full vigor and courage." Eventually excessive heat "[deprives] the body of all vigor and strength [and] then faintness is communicated to the mind [...]"(Montesquieu, 1750)

Carleton and Hsiang (2016) outline a general mechanism by which climate affects human activities: (1) Weather events are drawn from the probability distribution that determines the climate. (2) Each weather event generates an effect on a population and these events produce "responses" among the population. (3) Direct effects of weather events combine with nonclimactic factors to produce a distribution of observed data such as GDP. (4) People may alter their behavior in anticipation of weather events based on the information they are able to access. IPCC (2012) reports that "a changing climate leads to changes in the frequency, intensity, spatial extent, duration, and timing of extreme weather and climate events, and can result in unprecedented extreme weather and climate events." IPCC (2012) highlight three ways in which climate change might occur: (1) Through a shift in mean weather conditions but leaving the shape of the probability distribution intact (2) through an increase in variability (fatter tails, more extreme events) without a shift in the mean or (3) through a change in the shape of the probability distribution, such as being more skewed towards hotter temperatures. A shift in the climate probability distribution leads to changes in both the distribution of weather events and the distribution of social responses. A direct effect occurs as a result of a weather event (e.g. higher daily maximum temperatures), but people may also change their behavior (e.g. lowering the temperature on their thermostats), resulting in a shift in the distribution of observable outcomes that is a result of "a combination and interaction of these two effects." (Carleton and Hsiang, 2016)

2.2 The Impact of Climate on Socioeconomic Variables

A number of empirical studies show the effect that climate variables have on socioeconomic factors (Carleton and Hsiang, 2016). The human body regulates its temperatures so that bodily functions can continue to operate without any detrimental effects to health. Extreme temperatures affect increase stress on thermoregulatory systems and increase the risk of mortality (Huynen et al., 2001). It is thought that heat waves "displace mortality", whereby mortality rises during heat waves but falls in subsequent weeks, "principally [affecting] those whose health is already compromised and would have died in the short term anyway."(Huynen et al., 2001) The effects of colder temperatures seem to last longer and it is not known if there is a similar "mortality displacement" effect with cold spells (Guo et al., 2014). Guo et al. (2014) look at daily temperature and mortality rate data in 12 countries and find a relationship between ambient temperature and mortality. The 75th percentile of daily temperatures is associated with the lowest mortality rates while temperatures at the higher or lower extremes of the distribution are associated with higher risk of mortality (Guo et al., 2014). IPCC (2014b) Working Group I reports that "it is very likely that the number and intensity of hot days have increased markedly in the last three decades and virtually certain that this increase will continue into the late 21st century."(Olsson et al., 2014)

Climate has also been found to have an impact on civil conflict. Hsiang et al. (2011) find that the probability of new conflicts arising in tropical regions is double during El Niño years compared to La Niña years. Hsiang et al. (2011) challenge "the notion that random local temperature or rainfall shocks are analogues for global climate changes" because the global climate may interact with larger scale forces like conflict in ways that are not captured by daily average temperatures; global climate may also affect geopolitical factors on a larger scale than the areas captured by daily average temperatures, which may differ in different regions of a country; changes in climate are subject to less variability than changes in local weather, and the two may generate different social responses. Hsiang et al. (2011) find that the annual conflict risk of low-income countries is the most strongly correlated to the incidence of El Niño weather patterns. However, it is not known if low-income countries are more susceptible to climate-induced conflict because they are less able to buffer against environmental shocks or if countries have a lower income because they have historically been more sensitive to changes in climate or if there is an unobserved reason for the relationship between climate and conflict in low-income countries. Furthermore, Hsiang and Burke (2014) look at 50 quantitative studies on the relationship between climate and conflict and find that "the majority of studies suggest that conflict increases and social stability decreases when temperatures are hot and precipitation is extreme, but in situations where average temperature is already temperate, anomalously low temperatures may also undermine [social] stability." Hsiang and Burke (2014) also find that the relationship between climate and conflict holds for a range of temporal and spatial scales.

2.3 Climate and the Economy

In the climate-economy literature, there is a question regarding the distributional effects of changes in global climate.In 1992, Thomas Schelling writes in the American Economic Review that "[today] very little of our gross domestic product is produced outdoors, susceptible to climate. Agriculture and forestry account for less than 3 percent of GDP, and little else is affected. [...] Considering that in most developed countries [...] agricultural productivity for most parts of the world continues to improve, and that many crops and cultivated plants will benefit directly from enhanced photosynthesis due to increased carbon dioxide, one cannot be certain that the net impact on agricultural productivity will be negative or, if negative, noticed in the developed world." (Schelling, 1992) Schelling (1992) observes that there is a "mismatch" between the low-income countries that will be disproportionately affected by climate change and the high-income countries who are able to afford climate change mitigation. He notes that even if high-income countries were willing to invest heavily in greenhouse gas abatement technology, "it would be hard to make the case that the countries we now perceive as vulnerable would be better off 50 or 75 years from now if 10 or 20 trillions of dollars had been invested in carbon abatement rather than in their economic development."

Mendelsohn et al. (2000) find that climate-dependent sectors of the economy tend to have a hill-shaped relationship with temperature (Figure 2.2). This is corroborated with Burke et al. (2015)'s fitting of a non-linear relationship between temperature and GDP per capita growth (Figure 2.3).

The implication of a hill-shaped relationship between temperature and output or income is that "countries that happen to be in relatively cool regions of the world will likely benefit from warming and that countries that happen to be in relatively warm regions of the world will be harmed by warming." In fact, Burke et al. (2015) find optimal average annual temperature for GDP per capita to be 13 °C, which means that countries with an average annual temperature below 13 °C are likely to benefit from increasing average temperatures and countries with average annual temperature above 13 °C will have "damages" (reduced GDP per capita) from increasing average temperatures. However, we should note that changes in average temperatures, while a good index of the extent or severity of climate change impacts, do not reflect the heterogeneity of climate change impacts – "the results may be warmer in some places and colder in others, wetter in some places and drier in others, cloudier in some places and sunnier in others, stormier in some places and less stormy in others, – generally a complex of changes that would bear no easy relation to an average change in global temperature." (Schelling, 1992)

In the case of Mendelsohn et al. (2000), however, in estimating a climate response function for each country, they assume that climate change impacts each country in the same way, and only country characteristics differ. The authors generate country-specific response functions for five sectors likely to be affected by climate: agriculture, water, energy, timber and coasts, and

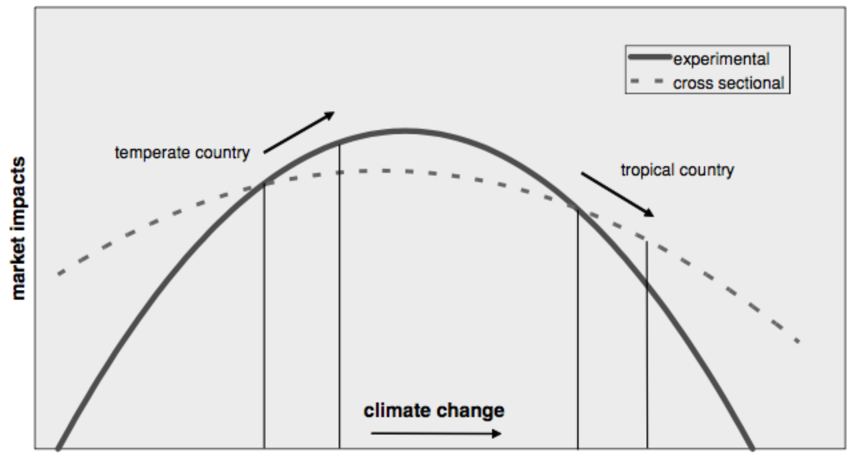

Figure 1. *Generic hill-shaped impact response function*

Figure 2.2
Hill-shaped Relationship Between Temperature and Climate-Dependent Economic Sectors, Figure 1, (Mendelsohn et al., 2000).

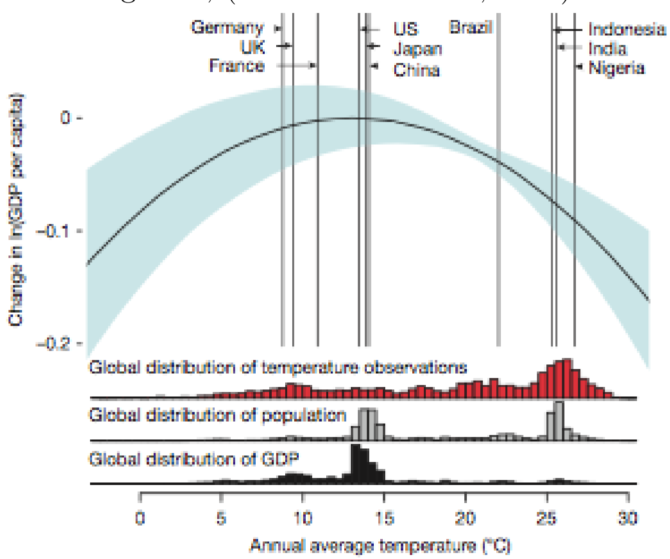

Figure 2.3
Non-linear Relationship Between Annual Average Temperature and ln(GDP per capita), Figure 2a, (Burke et al., 2015).

sum sectoral impacts to obtain an aggregate impact for each country. They report that "the poorest half of the world's nations suffer the bulk of the damages from climate change, whereas the wealthiest quarter has almost no net impacts." Mendelsohn et al. (2000) find that the coefficients for the relationship between temperature and GDP are "slightly different" between high and low-income countries. They report that "the developed country response function is both higher and flatter than the developing country response function, presumably because the high technology farmers have more capital and can substitute capital for climate. The model predicts that agriculture in developing countries is more vulnerable to higher than optimal temperatures."

Deryugina and Hsiang (2014) look at the relationship between daily temperature and county-level annual income in the US over a 40 year period and argue that even in a wealthy country like the US, "some economic vulnerabilities remain" and that "adapting to all climatic conditions along all margins is too costly." The US is particularly suitable for studying the effects of temperature on social variables because data is readily available and the land mass of the contiguous 48 states cover a range of climates and land cover types (Olsson et al., 2014). Deryugina and Hsiang (2014) use a difference-in-difference approach and find that an additional warm day (24-27 °C) reduces the average US county's per capita income by \$14.78 and an additional hot day (> 30 °C) reduces the average US county's per capita income by \$20.56. The relationship between temperature and daily per capita income is non-linear and Deryugina and Hsiang (2014) suggest that it is due to the effect of temperature on reducing the productivity of workers and crops.

2.4 Adaptation to Climate

In IPCC (2014a), adaptation is defined as "the process of adjustment to actual or expected climate and its effects." Adaptation depends on "adaptive capacity", which is determined by "socioeconomic characteristics." (IPCC, 2001) A system's vulnerability to external shocks is "a function of exposure, sensitivity and adaptive capacity." (Yohe and Tol, 2002) However, places with the greatest adaptive capacity are not necessarily the places that face the greatest exposure to climate change and vice versa. Furthermore, a country's adaptive capacity may differ depending on the type of climate event:

for instance, it may be relatively adaptable to changes in mean temperature but not very adaptable to increased frequency of tropical storms. Human societies have long had to develop various strategies for adapting to economic shocks related to the climate, from the migration of pastoralists to modern crop insurance schemes (Adger et al., 2003). In general, adaptation strategies include reducing dependence on economic activities that are likely to be heavily impacted by changes in climate (high-risk activities), such as shifting away from drought-prone crops, reducing sensitivity to climate, such as not building houses on floodplains, and fortifying existing infrastructure so as to mitigate damages from extreme weather events, such as building levees along the coast (Adger et al., 2003).

Adaptation to climate is complex because it involves the intertemporal valuation of the part of a country's welfare that is dependent on the climate, given vast uncertainty about the magnitudes of such changes, the interaction between different types of changes and time frame at which these changes are likely to take place (Stern et al., 2006). Furthermore, the actions that can be taken by each country is limited by the number of possible adaptation strategies. For instance, a country may have good public infrastructure but face a high-risk of suffering damages from climate shocks because of the geographical layout of important natural resources (Adger et al., 2003). Adger et al. (2003) list generic determinants of climate adaptive capacity as (1) social capital (the ability of a society to undertake collective action (Adger, 2001)) (2) responsiveness of government institutions (in terms of flexibility, innovation) (3) the ability of the private sector to take up opportunities that arise due to changes in the climate and (4) the resilience of groups that are at risk of climate-related damages.

Orlove (2005) describes episodes in the past where human societies adapted or failed to adapt to changes in climate: the Mayan civilization (250 - 900 A.D.), North Atlantic and Baltic Viking settlements (985 - 1430 A.D.) and the Dust Bowl era in the United States (mid. 20th century). All three societies had to develop novel ways of converting natural resources into economic inputs: the Maya used water storage to supplement their agricultural water supply and cut down forests to increase the amount of land available for agriculture; the Vikings had to adapt to new growing conditions in the places where they settled and supplemented their food supply with hunting game and during the Dust Bowl, farmers had to experiment with new crops and soil management techniques in order to accommodate drier growing conditions. Orlove (2005) cautions that there are limits to how much a society can adapt to changes in the climate, eventually both the Maya and the Vikings faced increased mortality and eventual abandonment of their settlements, partly due to insurmountable environmental challenges but also partly due to policies that contributed or exacerbated existing resource strains.

2.5 Machine Learning

It is, however, a challenge to "collapse large quantities of large of high-dimensional climate data into measures that efficiently summarize the dimensions of climate that are influential on specific aspects of populations." (Carleton and Hsiang, 2016) Dell et al. (2012) describe two approaches economists have used to quantify the effects of climate on economies: (1) Researchers have looked at the relationship between average temperature and aggregate economic variables using cross-sectional data and (2) researchers have looked at how different sectors of the economy respond to changes in climate and aggregated these effects to produce a net effect on the economy as a whole. These approaches face significant challenges. In the first instance, because other countries are not good counterfactuals for what would happen in a particular country in the absence of a change in average temperature, looking at the correlation between average temperatures and aggregate economic variables may produce "spurious associations of temperature with national characteristics such as institutional quality." In the second case, because of the complexity of national economies and climate systems, "[the] set of candidate of mechanisms through which temperature may influence economic outcomes is large and, even if each mechanism could be enumerated and its operation understood, specifying how they interact and aggregate poses substantial difficulties." (Dell et al., 2012) In the opening lines of his paper on the implications of increased frequency of extreme weather events ("fat tails"), Martin Weitzman says that "[climate] change is so complicated, and it involves so many sides of so many disciplines and viewpoints that no analytically-tractable model or paper can aspire to illuminate more than one or two facets of the problem." (Weitzman, 2011) Despite the challenges of quantifying the mechanisms by which climate might affect the economy, Hsiang and Burke (2014) suggest that "the absence of a single mechanistic explanation for the observed association does not mean we lack evidence of a causal association."

In their paper, *Temperature shocks and economic growth: Evidence from the last half century*, Dell et al. (2012) present us with an identification strategy that takes changes in country-level yearly average temperature as an exogenous shock and each country's outcome in a different year as a counterfactual for what would have happened in that country had the temperature shock not occurred. Dell et al. (2012) estimate that a 1 °C increase in average annual temperature reduces economic growth in a poor country by 1.3 percentage points. Dell et al. (2012) also look at shifts in annual average temperature between 1970 and 2000 and find that the coefficients are similar even though there are larger standard errors. Burke et al. (2015) use data from Dell et al. (2012) and fit a non-linear relationship between temperature and economic growth. Looking at various projections Shared Socioeconomic Pathway 5 (O'Neill et al., 2015), a relatively "optimistic" projection of future climate and socioeconomic outcomes given that fossil fuel reserves are abundant and global economies are increasingly integrated, Burke et al. (2015) estimate that increasing global average temperature will reduce global GDP by 23 %. In contrast, Mendelsohn et al. (2006)'s estimates for climate damages are a reduction of up to 23.8 % for the poorest quartile of countries, and smaller reductions and some gains for higher income countries.

With regards to the economic growth literature, in 1997, Xavier Sala-í-Martin ran two million regressions to determine which variables are "'significantly' correlated with growth." Sala-í Martin (1997) looked at 62 variables which were identified as relevant in the growth literature, selected 3 "robust" variables which he included in all regressions: national income, life expectancy and primary school enrollment and ran different combinations of the remaining 58 variables in sets of 3 to determine which variables are statistically significant "almost all of the time" (more than 90 percent of the time) and which variables are statistically significant 10 percent of the time or less. However, Sala-í Martin (1997) notes that the variables that he identifies are variables that are linearly-related to economic growth. In the case of climate change, there could be significant heterogeneity in "treatment effects," and, in the case of country-level aggregate data, "there may be many attributes of a unit relative to the number of units observed and where the functional form of the relationship between treatment effects and attributes of units is not known." (Athey and Imbens, 2016a) For instance, temperature may have a linear relationship with some factors of the economy and a nonlinear relationship with others.

To overcome difficulties in selecting relevant variables, fitting nonlinear models and dealing with large and complex datasets, Hal Varian suggests using machine learning techniques such as classification and regression trees, random forests and penalized regressions (Varian, 2014). Susan Athey and Guido Imbens (2016) outline a method for systematically dividing a dataset into subpopulations which can be used to estimate heterogeneous treatment effects. Each subpopulation is a "leaf" which forms part of a "tree", a series of optimized splits of the data. Researchers can set criteria for "pruning the tree" which include boundaries for how closely the "tree" fits the data (a minimum value for total Residual Sum of Squares) or a minimum "leaf size" criteria (a minimum number of observations in each "leaf") (Varian, 2014).

With increased processing power, researchers are able to run a large number of regressions involving a large number of observations and variables and "instruct" the computer to use certain criteria to parse the data and fit the data using linear or nonlinear models. In particular, with "supervised [machine] learning", researchers use a "training" dataset to generate a model that fits the data and use the model to generate predictions for a new dataset. Researchers can also "cross-validate" their model by using their model to make predictions for data within the original dataset that was not used to generate the model and seeing if their predictions are accurate based on existing data (Athey and Imbens, 2016b).

For this thesis, we use a technique known as "recursive partitioning." (Zeileis et al., 2008) In conventional regression trees, the outcome variable is predicted based on some value of the partitioning variables (Varian, 2014) and each terminal node is a collection of data points. In recursive partitioning, each terminal node is attached to a different parametric model (Zeileis et al., 2008). In conventional regression trees, the same model is used for the whole dataset, whereas in recursive partitioning, we are able to generate a different temperature response function for each set of countries.

Finally, we include a set of comparisons between total GDP per capita growth and agricultural GDP per capita growth because we recognize that agriculture is a sector that is important for growth in developing countries and agriculture is a sector that might be particularly sensitive to changes in temperature. In 1961, Johnston and Mellor (1961) highlight the role of agriculture in economic growth: (1) Failing to meet demands for food will be a serious impediment to growth (2) Expanding agricultural exports can be an important source of income, especially for developing countries (3) Agriculture is a key source of surplus labor for other sectors (4) Agriculture is a major sector in many countries and can be a source of capital for the development of other sectors (5) Rising incomes of farmers and rural populations can be a great boon for the economy. In more recent years, the World Bank and other groups have continued to emphasize the importance of agriculture as a driver of growth (World Bank, 2007).

Chapter 3

Model

3.1 Data Description

Our data is taken from Burke et al. (2015). The main outcome of interest is GDP per capita growth from the World Development Indicators dataset (World Bank, 2017). Our main predictors are temperature and precipitation aggregated at the year and country level from the University of Delaware's monthly gridded weather station data for air temperature and precipitation (Willmott et al., 2001). It should be noted that not all countries have observations for the entire time period (1960 - 2010) because some countries only came into existence after 1960 (e.g. former Soviet bloc countries) and GDP data is not available for some countries during years when there was conflict (e.g. Syria). We look at other variables that might determine countries' temperature response functions by importing time series data for (1) the share of a country's total GDP that is attributed to agriculture (Ag Share) (2) the percent of a country's population living in urban areas (Urbanization) and (3) Gini coefficient (Inequality). We use these variables as well as GDP (WDI) Percentile (Burke et al., 2015) (Income) and Share of GDP from the Agricultural sector to partition the dataset using the classification test described in Section 2.2. We use data from 2010 for all partitioning variables because it is the last year that appears in the Burke et al. (2015) dataset. We provide summary statistics for the dataset in Table 3.1.

Table 3.1
Summary Statistics

Whole Sample	
Median Temperature	18.67 °C
Median GDP Per Capita (2010)	$ 3,164
Median Ag Share (2010)	0.07
Median Inequality (2010)	33.76
Median Urbanization (2010)	0.87
Median Working Age Pop (2010)	0.64
Number of Countries	156
Number of Observations	6,584

3.2 Empirical Model

We use Burke et al. (2015)'s fixed effects model with quadratic terms for temperature and precipitation, as well as country-specific linear and quadratic time trends.

$$g_{it} = \theta_i + \theta_t + \alpha_1 T_{it} + \alpha_2 {T_{it}}^2 + \beta_1 P_{it} + \beta_2 {P_{it}}^2 + \theta_i \cdot t + \theta_i \cdot t^2 + \epsilon_{it}$$

g_{it} are country-year observations for GDP per capita growth, θ_i are country fixed effects, θ_t are year fixed effects, T_{it} and P_{it} are country-year observations for average temperature and precipitation, ${T_{it}}^2$ and ${P_{it}}^2$ are the squared terms for average temperature and precipitation, $\theta_i \cdot t$ is the country-specific linear time trend and $\theta_i \cdot t^2$ is the country-specific quadratic time trend. For our paper, we separate the dataset into different subgroups and run Burke et al. (2015)'s model on each subgroup separately.

3.3 Model-Based Recursive Partitioning

The most common tool used in applied econometrics for summarizing relationships in the data is linear regression analysis (Varian, 2014). As mentioned in Chapter 2, the challenge we face in the climate - economy literature is that relationships between climate variables and socioeconomic variables can be complex and it is difficult to collapse high-dimensional datasets "into measures that efficiently summarize the dimensions of climte that are influential on specific aspects of populations" (Carleton and Hsiang, 2016). Fortunately, we are able to use machine learning to supplement our econometric analyses and find x variables that provide us with a good prediction of y (Varian, 2014). There are many methods available, but in this paper, we will focus on regression trees and in particular, model-based recursive partitioning (Zeileis et al., 2008).

In 1963, Morgan and Sonquist (1963) presented us with a "radical new method for analyzing survey data" in the Journal of the American Statistical Association:

> The basic idea is the sequential identification and segregation of subgroups one at a time, nonsymmetrically, so as to select the set of subgroups which will reduce the error in predicting the dependent variable as much as possible relative to the number of groups. A subgroup may be defined as membership in one or more subclasses of one or more characteristics.

After going through this process for the entire dataset, we end up with a "tree" that shows us the variables which were used to split the dataset and the resulting subgroups (Fig. 3.2). The benefit of this approach is that it allows us to determine variables that are important to the analysis by detecting underlying relationships in the data, instead of prematurely simplifying our analysis by making "arbitrary or theoretical assumptions" (Morgan and Sonquist, 1963). We can then prevent overfitting of the data by setting parameters for determining what kind of splits we will allow. For instance, in our analysis, we find optimal splits by looking at the split (i.e. the value of the partitioning variable) that minimizes the total RSS of the two subgroups and we impose a 'minimum node size criteria' where subgroups must have at least 10 countries. This prevents our analysis from being skewed by countries that are very similar to each other that also have extreme values.

The most basic type of tree that we can generate is a classification tree. In a classification tree, the terminal nodes are defined by constants which we can use to predict the outcome variable. For example, Figure 1 in Varian (2014) shows us a classification tree for the survivors of the Titanic. The classification tree shows us that being older than 16 years of age and travelling in first class meant that you were likely to be a survivor. A more conventional approach to this problem in Economics would be to use a logit or probit model (Varian, 2014).

Classification trees are useful for answering questions about prediction, but if we wanted to answer questions about causal inference, we might want to fit each terminal node using a function instead of a constant. With model-based recursive partitioning (Zeileis et al., 2008), we generate a linear regression for each node, but this approach can also be used with maximum likelihood models. We plot the models associated with the terminal nodes in Figures 4.2 - 4.5.

Let x be a variable which we will use to partition the data. Let c be a value in x which we use as a threshold to partition the dataset. *Sample* is an indicator variable which determines which set of observations to run the regression over.

$$Sample = \begin{cases} 0, & \text{if } x > c \\ 1, & \text{if } x \leq c. \end{cases} \quad \forall c$$

At fixed intervals of c, run the regression if $Sample = 1$ and run another regression for $Sample = 0$ and calculate the residual sum of squares for each regression. Repeat for all x and find the value of c that minimizes the total residual sum of squares for both regressions. In Tables 3.2 - 3.4, we show the RSS values obtained from finding splits using different partitioning variables. We find that GDP Per Capita Percentile gives us the optimal first split for the dataset. Tables 3.3 and 3.4 show that historical mean temperature is the next optimal split for the low income and high income subgroups. We plot the total RSS values of using GDP Percentile (WDI) as the split variable for the entire dataset in Figure 3.1. Minimum total RSS is 17.42 and the value of GDP Percentile (WDI) that minimizes total RSS is 54.

In Figure 3.2, we show how the mean temperature split was obtained for the high income countries. The red line indicates the point where total residual sum of squares is minimized. In Figure 3.3, we show how the minimum node size constraint is applied for the mean temperature split for low income countries. The value that minimizes total RSS for the low income countries is 11 °C but this violates the minimum node size criteria and so we look for the next point in the data where there is the next largest change in total RSS, at 17 °C. In Figure 3.3, the original split value is indicated using the dashed line and the value we obtain after accounting for minimum node size is indicated using the red line. In Figure 3.4, we illustrate the splitting of the dataset into groups using a regression tree. We perform the Chow test on each split to test if the split is statistically significant. We find that all splits are statistically significant when we perform the Chow test on the coefficients for the linear and quadratic terms for temperature and precipitation, as well as year fixed effects.

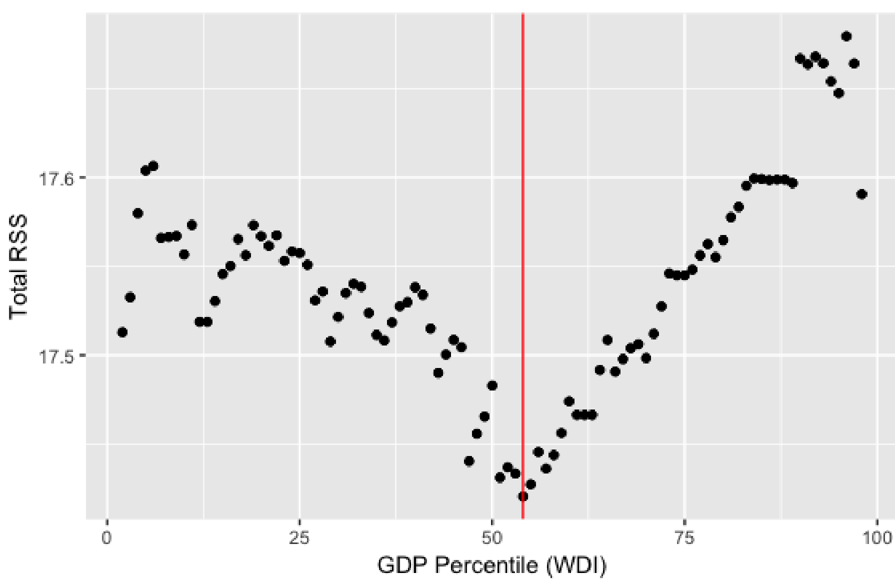

Figure 3.1
Total Residual Sum of Squares For GDP
Percentile (WDI) Values Used To Partition Dataset
Minimum RSS = 17.42, GDP Percentile = 54

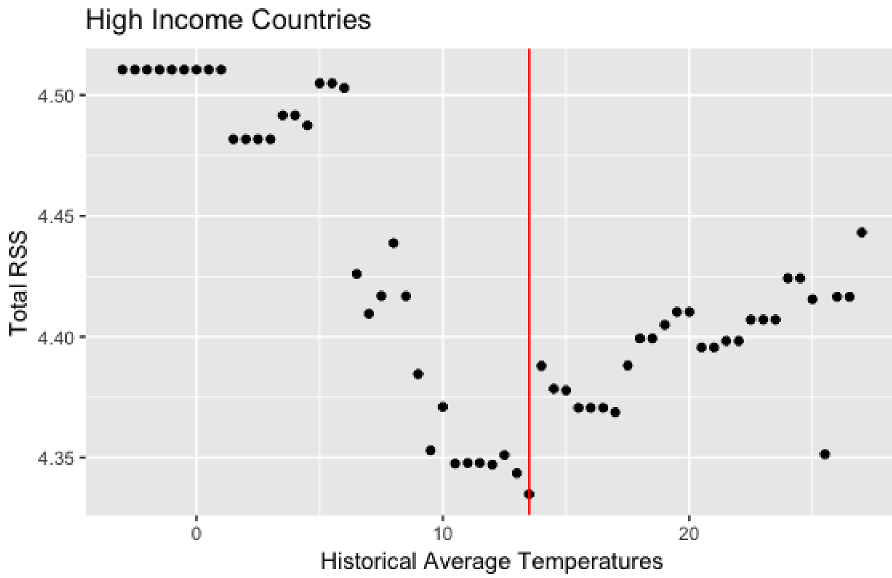

Figure 3.2
Total Residual Sum of Squares for Mean Temperature
Values Used to Partition High Income Countries

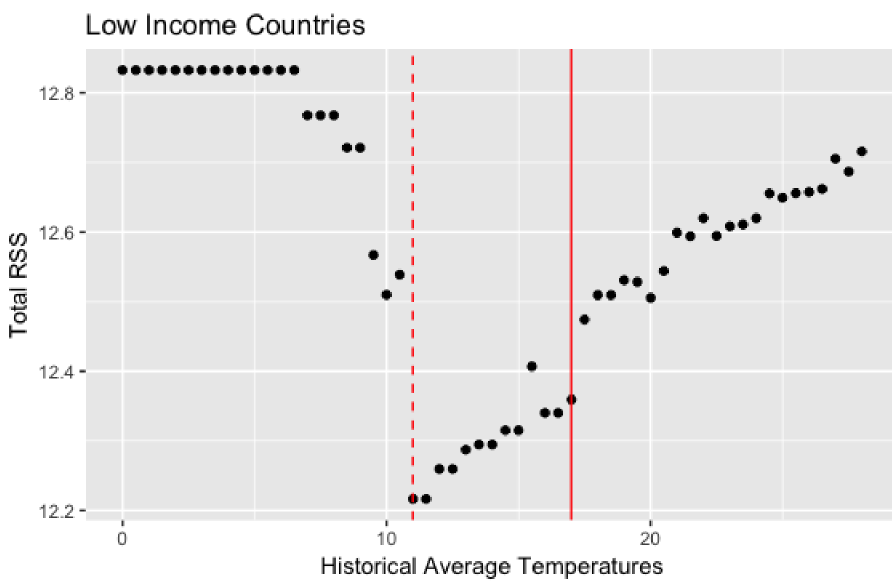

Figure 3.3
Total Residual Sum of Squares for Mean Temperature
Values Used to Partition Low Income Countries

Table 3.2
Split Values for Partitioning Over Entire Dataset

Split Variable	Split Value	Total RSS
Mean Temp	12.00	18.79
Ag Share (2010)	0.32	19.04
Urbanization (2010)	0.54	19.12
Inequality (2010)	42.32	19.01
GDP Per Capita Percentile (WDI)	54.00	17.43

Table 3.3
Split Values for Partitioning Over the Low Income Countries

Split Variable	Split Value	Total RSS
Mean Temp	17.00	12.37
Ag Share (2010)	0.33	12.72
Urbanization (2010)	0.67	12.80
Inequality (2010)	32.12	12.77
GDP Per Capita Percentile (WDI)	8.00	12.51

Table 3.4
Split Values for Partitioning Over the High Income Countries

Split Variable	Split Value	Total RSS
Mean Temp	13.50	4.33
Ag Share (2010)	0.02	4.42
Urbanization (2010)	0.87	4.39
Inequality (2010)	41.02	4.36
GDP Per Capita Percentile (WDI)	57.00	4.39

Low income countries are defined as countries whose GDP per capita are in the 53rd percentile and below. High income countries are defined as countries who GDP per capita are in the 54th percentile and above. Mean Temp is each country's mean annual temperature from 1950 - 2010. Ag Share is defined as the proportion of a country's total GDP that is attributed to agriculture. Urbanization is measured using the proportion of a country's population that lives in an urban area. Inequality is measured using the Gini coefficient for each country. We take calculate Ag Share using data already present in Burke et al. (2015)'s dataset and we obtain data for urbanization and inequality from the World Bank's Work Development Indicators dataset. We take our data for partitioning (with the exception of mean temperature) from the year 2010, because that is the most recent year that is present in our dataset.

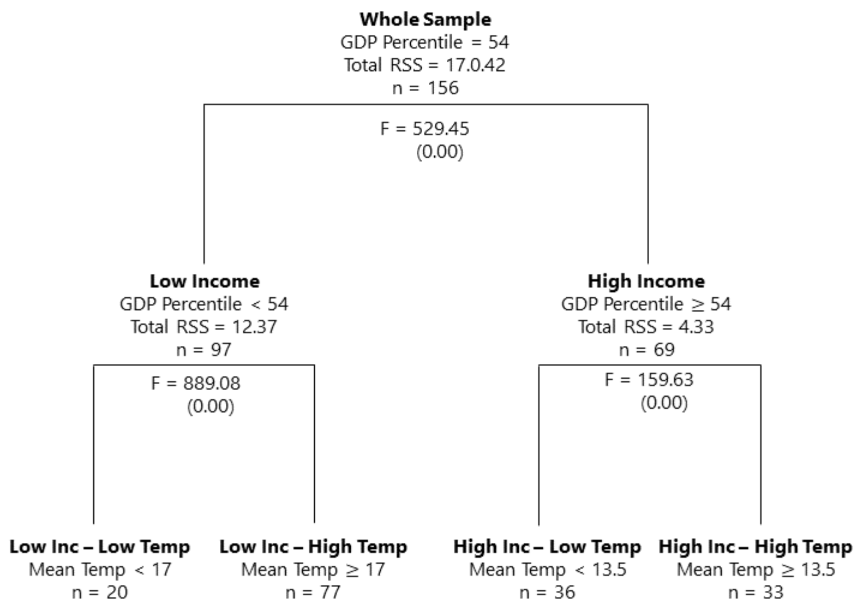

Figure 3.4
Regression Tree of Nonlinear Fixed Effects Model of Annual Average Temperature on GDP Per Capita Growth

In this figure, we show the criteria we used for splitting our sample of 156 countries into groups using a recursive partitioning algorithm (Zeileis et al., 2008). In the figure, we have included the residual sum of squares value of the split, which is the minimum RSS value compared to all the other possible splits using the same variable. 'n' refers to the number of countries in each group. We obtained F-statistics for each split by performing the Chow test, which tests for the statistical significance of splitting a dataset by testing the equality of coefficients on both sides of the split.P values for the F-statistic are included in parentheses.

Table 3.5
Summary Statistics for Terminal Nodes

Income Split		Low Income	High Income	
Median Temperature		24.12 °C	13.83 °C	
Median GDP Percentile		77	77	
Number of Countries		97	69	
Number of Observations		3,806	2,778	
Temp Split	Low Income		High Income	
	Low Temp	High Temp	Low Temp	High Temp
Median Temperature	12.04 °C	25.09 °C	8.76 °C	20.81 °C
Median GDP Percentile	34	35	83	70
Number of Countries	20	77	36	33
Number of Observations	612	3,194	1,366	1,412

Table 3.6
List of Countries in Terminal Nodes
Low Income Countries

Low Temp	High Temp	
Afghanistan	Angola	Liberia
Albania	Bangladesh	Madagascar
Armenia	Belize	Malawi
Azerbaijian	Benin	Malaysia
Bulgaria	Bolivia	Mali
Bosnia and Herzegovinia	Botswana	Mauritania
Belarus	Burkina Faso	Mauritius
Bhutan	Cabo Verde	Mozambique
China	Cambodia	Nepal
Georgia	Cameroon	Nicaragua
Iran	Central African Republic	Niger
Kyrgyzstan	Chad	Nigeria
Korea	Colombia	Oman
Lesotho	Comoros	Pakistan
Morocco	Democratic Republic of Congo	Papua New Guinea
Moldova	Cote d'Ivoire	Paraguay
Mongolia	Cuba	Phillippines
Tajikistan	Djibouti	Rwanda
Turkmenistan	Dominican Republic	Samoa
Uzbekistan	Egypt	Sao Tome and Principe
	Equatorial Guinea	Senegal
	Eritrea	Sierra Leone
	Ethiopia	Solomon Islands
	The Gambia	Sri Lanka
	Ghana	St Vincent
	Guatemala	Sudan
	Guinea	Swaziland
	Guinea-Bissau	Syrian Arab Republic
	Guyana	Tanzania
	Haiti	Thailand
	Honduras	Togo
	India	Tunisia
	Indonesia	Uganda
	Iraq	Vanuatu
	Jordan	Vietnam
	Kenya	Yemen
	Lao PDR	Zambia
		Zimbabwe

Table 3.7
List of Countries in Terminal Nodes
High Income Countries

Low Temp	High Temp
Austria	Algeria
Belgium	Argentina
Canada	Australia
Chile	The Bahamas
Croatia	Brazil
Czech Republic	Brunei Darussalam
Denmark	Costa Rica
Estonia	Cyprus
Finland	Ecuador
France	El Salvador
Germany	Fiji
Greenland	Gabon
Hungary	Greece
Iceland	Israel
Ireland	Japan
Italy	Kuwait
Kazakhstan	Lebanon
Latvia	Libya
Lithuania	Mexico
Luxembourg	Namibia
Macedonia	Panama
Netherlands	Peru
New Zealand	Portugal
Norway	Puerto Rico
Poland	Qatar
Romania	Saudi Arabia
Russian Federation	South Africa
Serbia	Spain
Slovak Republic	Suriname
Slovenia	Trinidad and Tobago
Sweden	United Arab Emirates
Switzerland	Uruguay
Turkey	Venezuela
Ukraine	
United Kingdom	
United States	

Chapter 4

Results

As seen in Figure 3.2, our data is split into 4 subgroups based on partitioning variables for income (GDP Percentile, WDI) and mean temperature (historical mean annual average temperature for each country). In Table 4.1, we show the regression coefficients and standard errors of the temperature and squared temperature variable when the data is split into these 4 subgroups. We find that the relationship between temperature and GDP per capita growth is highly significant when we run the regression on the whole sample, which lines up with the main findings of Burke et al. (2015). We find that the relationship between temperature and growth is being driven by high income countries, particularly countries which have low annual average temperatures. This lines up with Burke et al. (2015) as well: With an "optimum" temperature of 13 °C, the low temperature, high income countries are able to increase economic productivity as temperature increases and they approach the peak of the hill-shaped relationship between temperature and growth.(Fig. 3.1)

If the data does not correspond to an "adaptation" narrative, we expect that higher annual temperatures will produce negative effects on high temperature countries, regardless of income Burke et al. (2015), because they are on the negatively-sloped side of the hill-shaped relationship between temperature and growth. Without an "adaptation" narrative, we also expect low temperature countries to benefit from higher annual temperatures as they approach the "optimum" annual average temperature of 13 °C. If the data corresponds to an "adaptation" narrative, we expect that higher annual temperatures will have negative effects on low temperature countries, as they might have their own "optimum" temperature that is lower than the "global optimum" and so increasing temperatures may push them beyond their "local optimum" even as their temperatures are still below the "global optimum." With adaptation, we do not expect higher temperatures to be as damaging to high temperature countries because they might have a higher optimum temperature; in other words, because they are already adapted to high temperatures. The existing literature suggests that high income countries will be better able to respond to higher temperatures because they are already able to capitalize on the high temperatures they experience and they are, perhaps, less reliant on more temperature-sensitive sector like agriculture (IPCC, 2014b; Mendelsohn et al., 2006). So, we expect high income - high temperature countries to be less strongly affected by changes in temperature compared to the low income - high temperature countries. Our results suggest that countries are adapted to their historical temperatures and that we should take that into account when we think about climate change and rising average temperatures.

We seek to demonstrate that taking into account the heterogeneous responses countries have towards temperature is a necessary step for evaluating present and future impacts of climate change. First, we note that the temperature and growth relationship produces different coefficients in each of the terminal nodes and these coefficients differ from the ones we obtain when fitting the whole sample with one function (Table 4.1). Next, in Figure 4.2 and 4.3, we see that a homogeneous model for temperature and growth overestimates GDP per capita growth for high income countries and slightly underestimates GDP per capita growth for low income countries. We look at total GDP per capita growth and agricultural GDP per capita growth to see if agriculture might be a driving force in countries' responses to temperature. Finally, we generate projections for GDP per capita growth under different climate scenarios: (1) a 1 °C increase in annual average temperature for all countries (2) a 2 °C increase in annual average temperature for all countries (3) country-specific temperature changes for the year 2100 under the Relative Concentration Pathways (RCP) 8.5 climate scenario. The mean change in average annual temperature under RCP 8.5 is 4.17 °C. The minimum change is 2.68 °C (Cape Verde) and the maximum change is 5.78 °C (Finland).

When we look at the population-weighted average of global GDP per capita projections, we see that all groups suffer lower economic growth as a result of increased average temperatures. Our model allows us to look at how different groups of countries might be affected differently by projected changes in temperature. In Table 4.3, we see that projected increases in annual average temperature result in the largest damages for the low income - high temperature countries and the high income - low temperature countries. This is consistent with an interpretation where countries are adapted to the temperatures they have experienced historically and a similar change in annual average temperature can affect different countries differently.

For low income countries, those with high temperatures are likely to suffer damages from increased temperatures while low temperature countries are projected to benefit from increased temperatures. Low income - high temperature countries see their economic growth decrease from 2.69 % under the status-quo scenario to -3.19 % under year 2100 projections, whereas low income - low temperature countries see their economic growth fall from 5 % to 1.73 % in the year 2100.

For high income countries, our model predicts that high temperature countries will be able to maintain growth levels that are close to baseline and low temperature countries suffer growth that is close to zero in the year 2100. Under our calculation of the average GDP per capita growth for high income - high temperature countries, we see growth increasing from 1.97 % at baseline to 3.16 % in the year 2100 whereas for high income - low temperature countries, growth falls from 1.87 % at baseline to 0.00879 % in the year 2100.

In Table 4.4 and 4.5, we compare predicted values for the subgroups using Burke et al. (2015)'s model (allowing the temperature response function to be the same across countries) and our model (allowing the temperature response function to be different for each subgroup). We see that the models produce similar results for baseline temperatures but diverge under other climate scenarios. In the tables, we refer to Burke et al. (2015)'s model as 'BHM' and our model as 'Het'. The divergence between BHM and Het models gets larger as the temperature changes become more severe. Tables 4.4 and 4.5 show that differing hypotheses of temperature response will lead to different expectations about the future and, perhaps, different actions being undertaken to mitigate or adapt to temperature changes. BHM overestimates growth for low income - low temperature, low income - high temperature and high income - low temperature countries. BHM underestimates growth for high income - high temperature countries.

In Figures 4.2 - 4.3, we plot predicted values given for BHM and Het models given historically observed temperatures. For each node, we plot the median of the mean temperatures in the group. In Figure 4.2, we see that BHM predicts maximum growth at around the median temperature of the group. However, we see that the Het model has a much flatter hill-shaped relationship for the high income countries. In Figure 4.3, we see that BHM and Het models both predict that low income countries have declining growth as average annual temperatures increase, especially since most of the countries in the group are on the negatively-sloped side of the curve.

In Figures 4.4 and 4.5, we plot predicted values for each terminal node for historically observed annual temperatures and compare them with predicted values under BHM. We see that the high temperature countries in both groups tend to follow linear relationships between temperature and growth whereas low temperature countries seem to have nonlinear relationships between temperature and growth. High income - high temperature countries have a positive relationship with annual average temperatures whereas low income - high temperature countries have a negative relationship with annual average temperatures. In Figure 4.4, maximum growth for high income - low temperature countries is at 9 °C whereas maximum growth predicted by BHM is 14 °C and maximum growth predicted by our model for high income countries is at 17 °C. In Figure 4.5, low income - low temperature countries have maximum growth at 13 °C whereas maximum growth predicted by BHM is at 14 °C and maximum growth predicted by our model for low income countries is at 16 °C. These results indicate that low temperature countries have a lower optimal temperature for growth and high temperature countries have a higher optimal temperature for growth.

In Figure 4.6, plot total GDP per capita growth and agricultural GDP per capita growth to see if the agricultural sector has a different response to temperature compared to the economy as a whole. In Figure 4.6 we see that, as a whole, agricultural GDP seems to have a steeper relationship with temperature compared to the rest of the economy. In Tables 4.6 and 4.7, we see that agricultural GDP tends to have larger coefficients for the temperature and squared temperature term. Subsgroups that have a statistically significant relationship between temperature and total GDP per capita growth also had statistically significant relationships between temperature and agricultural GDP per capita growth. For the high income - high temperature countries, however, the relationship between temperature and total GDP growth is not significant whereas the relationship between temperature and agricultural GDP is marginally significant ($p = 0.077$).

In Table 4.8 and 4.9, we compare predictions for agricultural GDP per capita growth and total GDP per capita growth under different temperature change scenarios. Looking at the BHM predictions, we see that while total GDP is predicted to have positive growth under climate change scenarios, agricultural GDP is predicted to have negative growth under climate change scenarios. The low temperature countries are projected to suffer more damages in terms of agricultural GDP. If agriculture is adapted to certain ranges of temperature, then veering beyond those physiological boundaries could be detrimental to agricultural output. However, our data makes predictions based on data from the past and does not account for colonization of land that was previously permafrost by species that were hitherto unable to survive in low temperature countries.

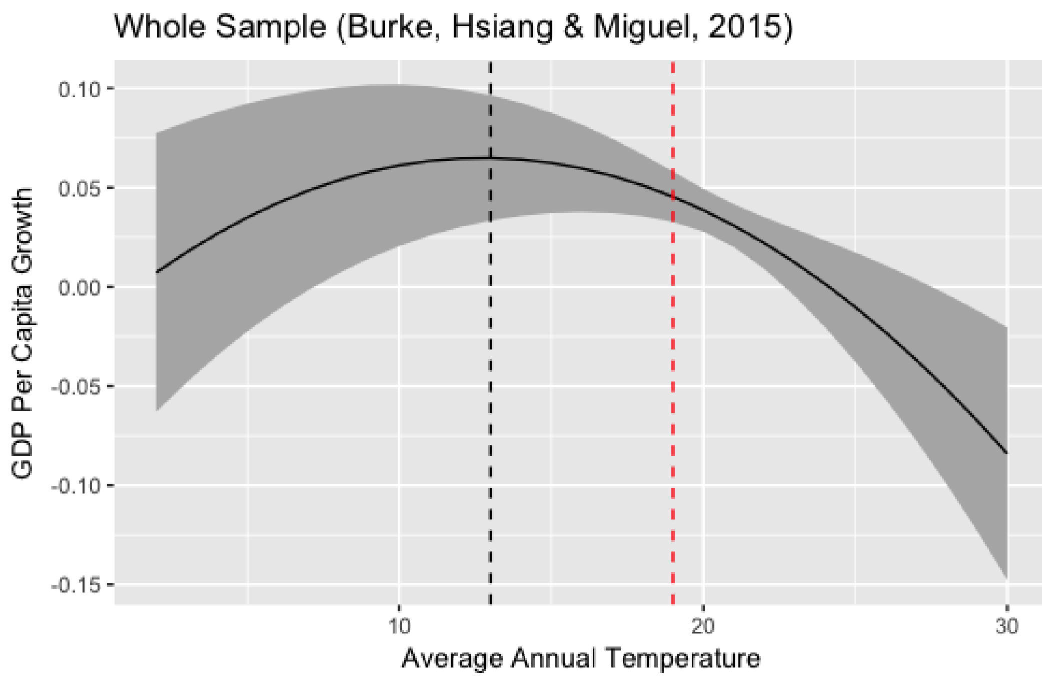

Figure 4.1
Predicted Values for GDP Per Capita Growth Using Whole Sample
(Burke et al., 2015)

The black dotted line indicates the annual average temperature of 13 °C, which is found to be the most productive by Burke et al. (2015). The red dotted line indicates the median temperature.

Table 4.1
Fixed Effects Regression Results Using Splits
Determined By Classification Tests
Low Income Countries

	Whole Sample	Low Income	Low Income	
			Low Temp	High Temp
Temp	0.0210**	0.0114	0.0350	-0.0059
	(0.0084)	(0.0226)	(0.0233)	(0.0251)
$Temp^2$	-0.0008***	-0.0006	-0.0014	-0.0002
	(0.0002)	(0.0005)	(0.0011)	(0.0005)

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4.2
Fixed Effects Regression Results Using Splits
Determined By Classification Tests
High Income Countries

	Whole Sample	High Income	High Income	
			Low Temp	High Temp
Temp	0.0210**	0.0214**	0.0109***	0.0029
	(0.0084)	(0.0085)	(0.0023)	(0.0181)
$Temp^2$	-0.0008***	-0.0008**	-0.0006***	-4.2E-6
	(0.0002)	(0.0003)	(0.0001)	(0.0005)

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4.3
Population-Weighted Average Global GDP Per Capita Growth

	Without Splits (BHM, 2015)	Income Split	Temp Split
1960 - 2010 Temperatures	3.44%	3.43%	3.43%
1 °C Increase	2.84%	2.82%	2.72%
2 °C Increase	2.16%	2.07%	1.80%
RCP 8.5 Year 2100 Projection	0.0317%	0.00227%	-0.0482%

Table 4.4
Population-weighted Average GDP
Per Capita Growth For Terminal Nodes

	Without Splits	Low Income	
	(BHM,2015)	Low Temp	High Temp
1960 - 2010 Temperatures	3.44%	6.36%	2.69%
1 °C Increase	2.84%	5.89%	1.31%
2 °C Increase	2.16%	5.15%	-0.112%
RCP 8.5 Year 2100 Projection	0.0317%	1.73%	-3.19%
No. of countries	156	20	77
No. of Obs.	6,584	612	3,194

	Without Splits	High Income	
	(BHM,2015)	Low Temp	High Temp
1960 - 2010 Temperatures	3.44%	1.87%	1.97%
1 °C Increase	2.84%	2.26%	1.69%
2 °C Increase	2.16%	1.40%	2.55%
RCP 8.5 Year 2100 Projection	0.0317%	0.00879%	3.16%
No. of countries	156	36	33
No. of Obs.	6,584	1,366	1,492

Table 4.5
Population-Weighted Average GDP Per Capita Growth
For Low Income Countries
Comparing Burke et al. (2015) and Heterogenous Model for Terminal Nodes

	Low Income			
	Low Temp		High Temp	
	BHM	Het	BHM	Het
1960 - 2010 Temperatures	6.36 %	6.36 %	2.69 %	2.69 %
1 °C Increase	6.22 %	5.89 %	1.49 %	1.31 %
2 °C Increase	5.98 %	5.15 %	0.0194 %	-0.112 %
RCP 8.5 Year 2100 Projection	4.83 %	1.73 %	-2.79 %	-3.19 %
No. of Countries	20	20	77	77
No. of Obs.	612	612	3,194	3,194

Table 4.6
Population-Weighted Average GDP Per Capita Growth
For High Income Countries
Comparing Burke et al. (2015) and Heterogenous Model for Terminal Nodes

	High Income			
	Low Temp		High Temp	
	BHM	Het	BHM	Het
1960 - 2010 Temperatures	1.87 %	1.87 %	1.98 %	1.97 %
1 °C Increase	2.07 %	1.69 %	1.40 %	2.26 %
2 °C Increase	2.18 %	1.40 %	0.0743 %	2.55 %
RCP 8.5 Year 2100 Projection	2.02 %	0.00879 %	-0.0988 %	3.16 %
No. of Countries	36	36	33	33
No. of Obs.	1,366	1,366	1,492	1,492

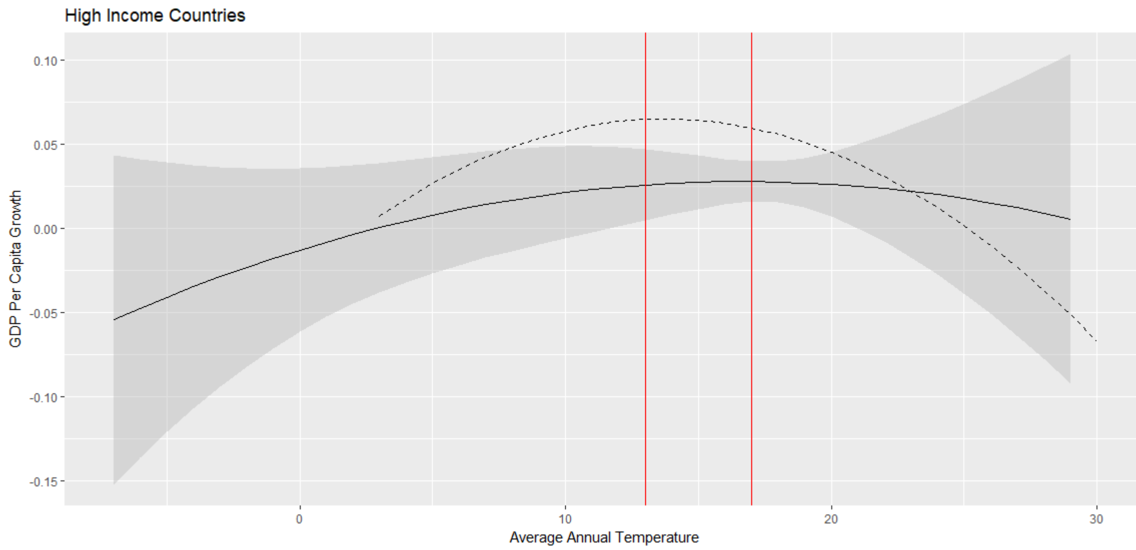

Figure 4.2
Predicted GDP Per Capita Growth for High Income Countries

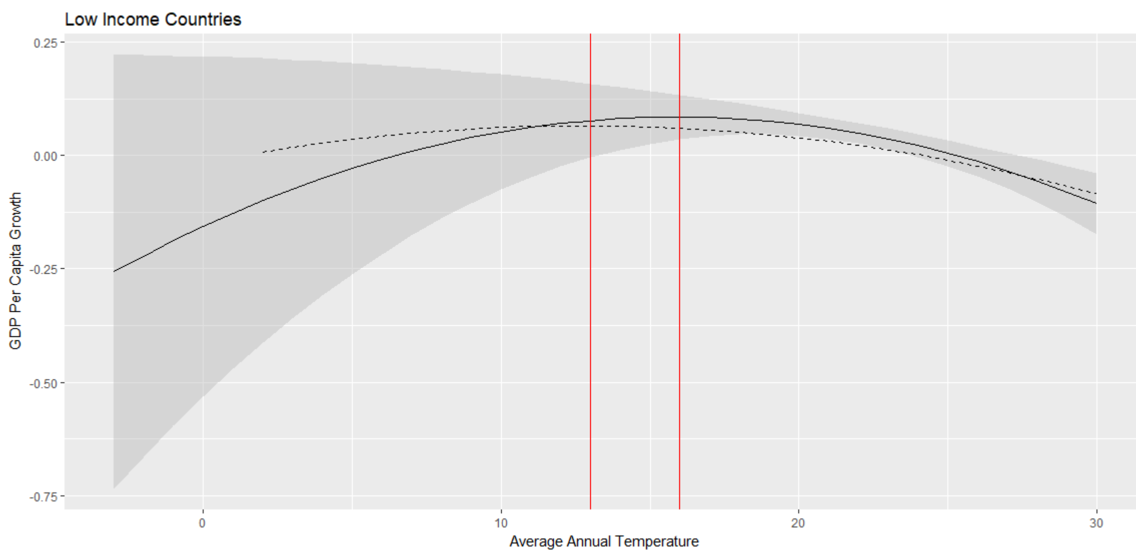

Figure 4.3
Predicted GDP Per Capita Growth for Low Income Countries

The black line indicates predicted values for high income countries under our model and the dotted line indicates predicted values for all countries under BHM. Red vertical lines indicate temperatures at which maximum growth occurs under our model and BHM. Shaded areas indicate the 95 % confidence interval for predicted GDP per capita growth values. For high income countries, maximum growth occurs at 17 °C under our model and for low income countries, maximum growth occurs at 16 °C. Under BHM, maximum growth occurs at 13 °C.

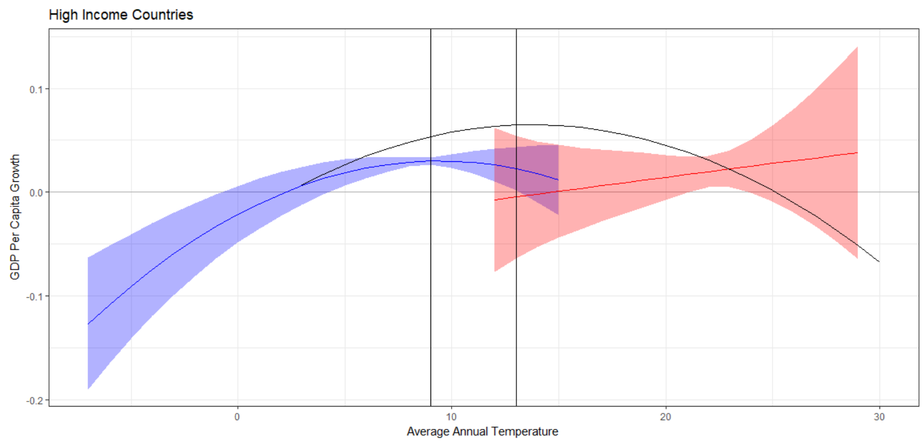

Figure 4.4
Predicted GDP Per Capita Growth for High Income Countries
With Mean Temp Split

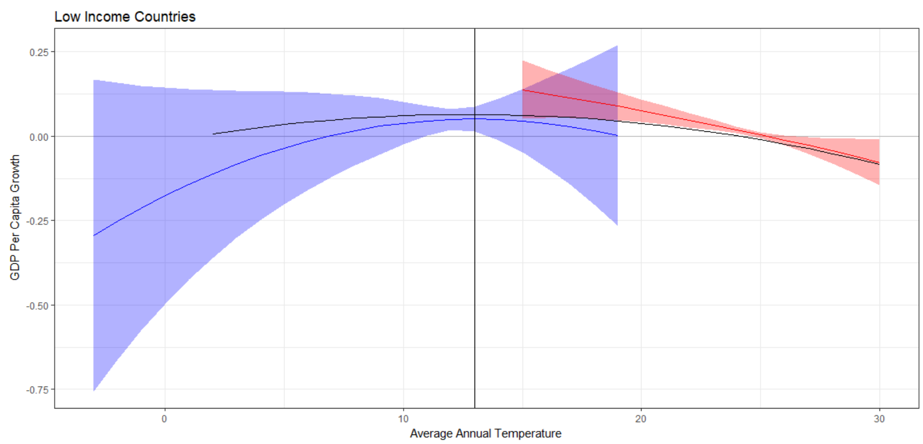

Figure 4.5
Predicted GDP Per Capita Growth for Low Income Countries
with Mean Temp Split

The black line indicates predicted values for the high income or low income countries under BHM. The blue line indicates predicted values for low temperature countries and the red line indicates predicted values for high temperature countries. Shaded areas indicate the 95 % confidence interval for predicted GDP per capita growth values. Red vertical lines indicate temperatures at which maximum growth occurs under our model and BHM. Predicted values for growth are linear and positive for high income - high temperature countries and linear and negative for low income - high temperature countries. Maximum growth occurs at 9 °C for high income - low temperature countries and 13 °C for low income - low temperature countries. Under BHM, maximum growth occurs at 13 °C.

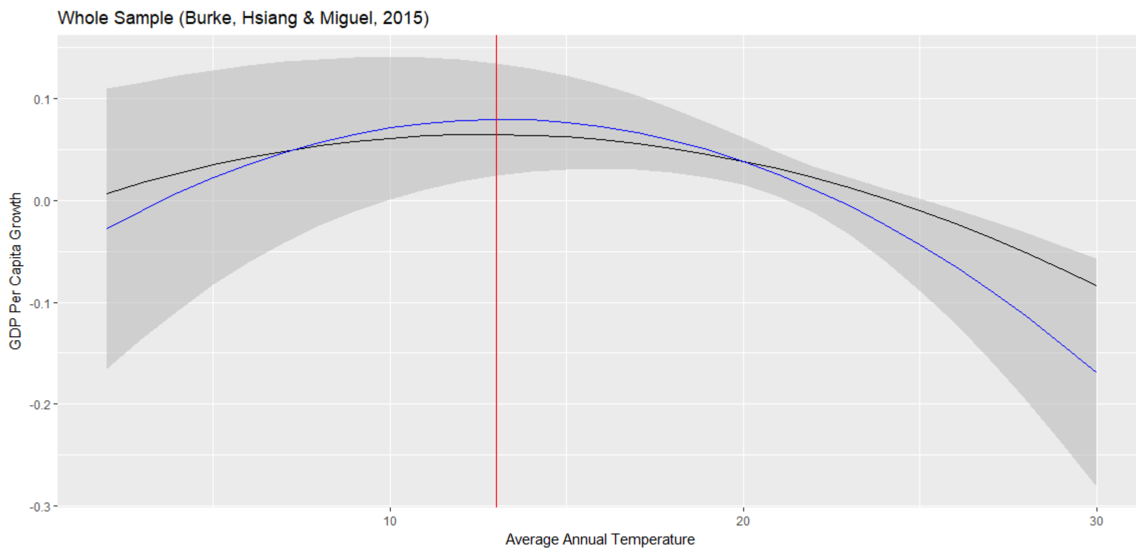

Figure 4.6
Predicted Values for GDP Per Capita Growth
and Agricultural GDP Per Capita Growth Using the Whole Sample

The black line represents total GDP per capita growth while the blue line represents agricultural GDP per capita growth. The shaded area represents the 95 % confidence interval for predicted values of agricultural GDP per capita growth. The dotted line represents the median temperature of the whole sample. Maximum growth for both total and agricultural GDP per capita occurs at 13 °C.

Table 4.7
Fixed Effect Regression Results Using Total GDP Per Capita Growth and Agricultural GDP Per Capita Growth For Low Income Countries

	No Splits (BHM, 2015)		Low Inc - Low Temp	
	GDP	Ag GDP	GDP	Ag GDP
Temp	0.0127***	0.0224**	0.0348	0.0285
	(0.003)	(0.009)	(0.023)	(0.032)
$Temp^2$	-4.87E-04***	-8.56E-04***	-1.36E-03	-1.75E-03
	(1.18E-04)	(2.62E-04)	(0.001)	(0.001)
Precip	1.44E-05*	8.46E-05***	-1.48E-05	2.08E-04
	(1.01E-05)	(2.69E-05)	(3.71E-05)	(1.61E-04)
$Precip^2$	-4.73E-09	-1.94E-08***	-3.22E-09	-3.46E-08
	(2.56E-09)	(6.81E-09)	(5.07E-09)	(2.81E-08)
No. of countries	156	156	20	20
No. of obs.	6,584	6,584	612	612

Standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.10.

	No Splits (BHM, 2015)		Low Inc - High Temp	
	GDP	Ag GDP	GDP	Ag GDP
Temp	0.0127***	0.0224**	-0.00316	-0.0383
	(0.003)	(0.009)	(0.026)	(0.061)
$Temp^2$	-4.87E-04***	-8.56E-04***	-2.10E-04	3.12E-04
	(1.18E-04)	(2.62E-04)	(5.60E-04)	(0.00124)
Precip	1.44E-05*	8.46E-05***	3.16E-05**	0.000130***
	(1.01E-05)	(2.69E-05)	(1.44E-05)	(0.0000287)
$Precip^2$	-4.73E-09	-1.94E-08***	-9.55E-09***	-3.23E-08***
	(2.56E-09)	(6.81E-09)	(3.46E-09)	(7.78E-09)
No. of countries	156	156	77	77
No. of obs.	6,584	6,584	3,194	3,194

Standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.10.

Table 4.8
Fixed Effect Regression Results Using Total GDP Per Capita Growth and Agricultural GDP Per Capita Growth For High Income Countries

	No Splits (BHM,2015)		High Inc - Low Temp	
	GDP	Ag GDP	GDP	Ag GDP
Temp	0.0127***	0.0224**	0.0112***	0.0378***
	(0.003)	(0.009)	(0.002)	(0.011)
$Temp^2$	-4.87E-04***	-8.56E-04***	-5.91E-04***	-2.22E-03***
	(1.18E-04)	(2.62E-04)	(1.57E04)	(5.48E-04)
Precip	1.44E-05*	8.46E-05***	5.49E-05***	8.77E-05
	(1.01E-05)	(2.69E-05)	(4.02E-05)	(1.36E-04)
$Precip^2$	-4.73E-09	-1.94E-08***	-3.90E-08*	-4.99E-08
	(2.56E-09)	(6.81E-09)	(2.30E-08)	(7.61E-08)
No. of countries	156	156	36	36
No. of obs.	6,584	6,584	1,366	1,366

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

	No Splits (BHM,2015)		High Inc - High Temp	
	GDP	Ag GDP	GDP	Ag GDP
Temp	0.0127***	0.0224**	0.00337	-0.0742*
	(0.003)	(0.009)	(0.018)	(0.040)
$Temp^2$	-4.87E-04***	-8.56E-04***	-1.24E-05	1.53E-04
	(1.18E-04)	(2.62E-04)	(4.80E-04)	1.09E-03)
Precip	1.44E-05*	8.46E-05***	1.39E-05	1.52E-05
	(1.01E-05)	(2.69E-05)	(2.17E-05)	5.13E-05
$Precip^2$	-4.73E-09	-1.94E-08***	-2.53E-09	-3.23E-09
	(2.56E-09)	(6.81E-09)	(4.36E-09)	(9.04E-09)
No. of countries	156	156	33	33
No. of obs.	6,584	6,584	1,412	1,412

Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4.9
Population-Weighted Projected Values for Total GDP Per Capita Growth and Agricultural GDP Per Capita Growth For Low Income Countries

	No Splits		Low Income			
	(BHM, 2015)		Low Temp		High Temp	
	GDP	Ag GDP	GDP	Ag GDP	GDP	Ag GDP
1960 - 2010 Temperatures	3.44%	-6.14%	6.36%	2.49%	2.69%	4.66%
1 °C Increase	2.84%	-7.19%	5.89%	0.24%	1.31%	2.41%
2 °C Increase	2.16%	-8.41%	5.15%	-2.35%	-0.11%	0.23%
RCP 8.5 Year 2100	0.32%	-11.68%	1.73%	-11.23%	-3.19%	-4.12%
No. of countries	156	156	20	20	77	77
No. of obs.	6,584	6,584	612	612	3,194	3,194

Table 4.10
Population-Weighted Projected Values for Total GDP Per Capita Growth and Agricultural GDP Per Capita Growth For High Income Countries

	No Splits		High Income			
	(BHM, 2015)		Low Temp		High Temp	
	GDP	Ag GDP	GDP	Ag GDP	GDP	Ag GDP
1960 - 2010 Temperatures	3.44%	-6.14%	1.87%	2.71%	1.97%	13.05%
1 deg. C increase	2.84%	-7.19%	1.69%	1.64%	2.26%	11.41%
2 deg. C increase	2.16%	-8.41%	1.40%	0.12%	2.55%	10.07%
RCP 8.5 Year 2100	0.32%	-11.68%	0.09%	-5.90%	3.16%	8.15%
No. of countries	156	156	36	36	33	33
No. of obs.	6,584	6,584	1,366	1,366	1,412	1,412

Chapter 5

Implications and Conclusion

The main contribution of our paper to the climate-economy literature is that we use a data-driven approach to fit multiple functions in the same dataset and in so doing, we are able to formally corroborate many ideas that are often discussed in the literature but less often demonstrated. Our results support that of Dell et al. (2012) and Mendelsohn et al. (2006), which find that higher temperatures lead to reduced growth in low income countries. With Burke et al. (2015) and Dell et al. (2012), we note that our data only accounts for the effect that temperature has on GDP per capita growth and not other effects on society that may come about due to increased annual average temperatures e.g. rising sea levels, increased frequency of extreme weather events, etc. Our results also do not account for important within - country heterogeneities which play an important role in the average person's experience of changes in climate, especially for larger countries that encompass multiple climate and agroecological zones. It may be that hotter regions within a country will react to temperature changes differently than colder regions within a country (Deryugina and Hsiang, 2014). We also recognize that we have adopted a largely empirical approach and have made the assumption that including country fixed effects and country-specific linear and quadratic time trends accounts for other factors such as education or technology. A worthy avenue of further research would be developing theoretical economic models that account for the impact of climate on society. Furthermore, we also note that our projections were made based on countries' historical responses to changes in the annual average temperature. There should be a degree of caution when extrapolating beyond the temperature ranges countries have experienced. However, rising temperatures are likely to be a reality for many countries and so we add our work to the rest of the literature that aims to aid in efforts to prepare for the effects of anticipated temperature changes.

We find that low income - high temperature and highly agricultural countries are at risk of negative GDP per capita growth as a result of projected temperature changes (Table 4.4). Dube et al. (2016) relates the impact of climate change on local livelihoods in different African countries to regional and continental impacts and finds that because a large proportion of people in African countries are engaged in agricultural activities, the effect of a bad harvest or a drought is much more strongly felt. The effects become stronger if the country is a low income country that may not have the infrastructure necessary to adapt to or mitigate the deleterious effects of changing temperatures (IPCC, 2014b). Our findings support the many calls for increased efforts to help vulnerable groups begin adapting to the climatic changes that are already beginning to materialize.

In Table 4.4 and 4.5, we look at the differences in projected average GDP per capita growth for terminal nodes according to the model used by Burke et al. (2015) and our model. We note that the models produce similar projections for baseline temperatures and differ greatly when it comes to projected impacts of temperature in the year 2100. Burke et al. (2015) predict that low income - low temperature countries will retain high levels of growth (4.83 %) whereas our model predicts that low income - low temperature countries will have low growth in 2100 (1.73 %). Both models predict negative growth for the low income - high temperature countries in the year 2100.

For high income - low temperature countries, Burke et al. (2015)'s model predicts that growth will not change much from baseline levels (2.02 %) whereas our model predicts reduced growth (0.00879 %). For high income - high temperature countries, Burke et al. (2015)'s model predicts negative growth (-0.0988 %) whereas our model predicts positive growth (3.16 %).

The implication of our results is that we are to expend our resources to help countries mitigate the damages from climate change, accounting for adaptation will be an important consideration for which countries these efforts are directed to. If we do not consider adaptation and only look at the general effects of temperature on countries, we will want to direct our investments to high temperature countries. If we consider adaptation to historical mean temperatures, we will want to direct our investments to low income countries but high income - low temperature countries should also make mitigation a priority. High income - high temperatures are not projected to suffer damages under our model, but we should note that the RCP 8.5 scenario assumes "modest technological growth" and reliance on coal and increased scarcity of oil and gas (Riahi et al., 2011).

We find that under BHM, agricultural GDP will suffer up to 11.68 % decline in the year 2100 overall. In our analysis, the low income countries and the high income - low temperature countries will experience negative growth whereas high income - high temperature countries will experience high growth in agriculture. Our projections show that the bulk of the damages are borne by the low income - low temperature countries (-11.23 %), followed by the high income - low temperature countries (-5.90 %) and the low income - high temperature countries (-4.12 %). As to how likely these changes are to occur, the discussion hinges on whether or not plant species will be able to adapt to new conditions or "move northward" as lands that were formerly too cold for cultivation become warmer. Pecl et al. (2017) consider the impacts of the migration of biodiversity under climate change. They note that terrestrial species have been moving towards colder regions at a rate of 17 kilometers per decade and marine species 72 kilometers per decade. However, even as some flora and fauna are able to migrate to more suitable habitats, humans, who rely on technology to overcome environmental constraints might not be able to move as easily to places where they might be able to take advantage of better agricultural prospects. Furthermore, there is a web of complex interactions between changing temperature, food supply (e.g. coffee, Atlantic salmon) and economic growth that is beyond the scope of this paper.

One feature of the time period we study that is unique is the dissolution of the Soviet Union that occurred in the 1990s. After 1991, there were a number of new countries that were formed that are in the same geographical region and were subject to similar economic policies for a number of decades. The central Asian countries experienced similar patterns in the 1990s – "skyrocketing inflation, partial de-industrialization and the collapse of Soviet-style welfare systems" (Batsaikhan et al., 2017). 15 of the countries in our dataset are former Soviet Union countries (including Russia) and 9 out of the 15 belong to the low income group of countries and all of them are low temperature countries. In this paper, we have chosen to keep the former Soviet countries in our analysis but we should treat the projections for low income - low temperature countries as a lower bound for climate damages because of the effect the former Soviet countries might have had on our predictions.

Finally, Mahapatra and Ratha (2017) argue that the Paris Climate Accord still has “miles to go” in moving countries to a low-carbon pathway because of the “absence of actionable commitments, discord on sharing of remaining carbon space, disagreement over finance, lack of clarity and sidelining the least developed and vulnerable countries.” Our results suggest that high income countries should not be complacent about the projected effects of climate change and investments in mitigation will be beneficial to both high income and low income countries.

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