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Essays on the Impact of Climate Change and Determinants of Climatological Damages

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SETTORE SCIENTIFICO DISCIPLINARE DI AFFERENZA: SECS-P/01; SECS-P/05; SECS-P/06

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Introduction

My dissertation comprises of a collection of four individual papers studying climate change impacts. I use econometric techniques to quantify the impact of climate change and variability on crop yields and health, and to analyze the socio-economic determinants of climatological disasters. All these domains are extremely sensitive to changes in the climatic factors which affect crucial aspects of human existence and welfare and are likely to result in important economic consequences. Personally, being from Bangladesh - one of the most vulnerable countries to climate change - I experienced concretely how health, agriculture, and extreme events impacts are related to the very concept of well-being. I am thus convinced that quantifying these impacts with robust methodologies is the necessary first step towards a global consensus to tackle climate change.

While a great deal of the existing literature in the field has adopted a global-aggregated perspective, my goal is in particular to examine and emphasize on the differentiated or uneven distribution of impacts across countries.

My final aim is not only to contribute to the academic debate but also to aid policymakers in decision-making with concrete quantitative evidence. A further value added of the work is to apply a methodology that, albeit used here to study specific problems, is flexible enough to be applied to many other forms of climate change impacts.

The first chapter provides evidence of robust non-linear effects of both temperature and specific humidity on influenza mortality rates in the U.S. Using weekly data at the city level; we utilize Generalized Additive Models to investigate the relationship between climatic variables and influenza mortality rates in 122 cities during 1970 - 2010. Our results provide empirical support to epidemiological experiments under laboratory conditions stating that the highest risk of influenza is at extreme low and high temperatures ranges and at specific humidity levels between 4 g/kg and 12 g/kg (equivalent to Relative Humidity of 23% and 70%). Furthermore, using bias-corrected methodology, we provide projections of influenza mortality for the U.S. and find that the West, Midwest, and the Southeastern parts of the country will be at high risk of influenza mortality by the end of the 21st century - with mortality increasing by up to 3% in some areas. This paper is co-authored with Professor Ian S. Wing, Boston University.

The second chapter, using an updated global malaria mortality dataset for 105 countries between 1980 and 2010 and Quantile regressions finds that the optimal temperature for countries with low malaria mortality is 32.6°C - slightly higher than previous estimates. However, the optimal temperature estimated for countries with relatively high malaria mortality is 24.07°C, lower than that suggested by existing estimates. This is one of the first papers to provide global scale empirical evidence that the effect of temperature and precipitation on malaria mortality is non-linear. It can offer useful insights to identify those regions near the vulnerability threshold of optimal temperature and precipitation levels for malaria mortality and thus areas at higher risk of future malaria outbreaks.

Chapter 3 combines historical crop yield data for rice and maize with corresponding temperature and precipitation data during 1971-2012 to study the impact of changes in climate variability. Using Quantile Regression, we find that increases in variability of both temperature and precipitation may benefit crop yields up to a certain degree; however, as the variability exceeds a certain threshold, it is expected to have a negative impact. The results demonstrate that temperature variability beyond 0.57°C (0.72°C for maize) will negatively impact rice yield in low yield countries while rainfall variability beyond 178 mm (192 mm for maize) would also be detrimental. While growth of crops usually acclimatizes to long-term means and adjusts with moderate variations, high degrees of climatic variability seem to have a negative effect.

The final chapter, co-authored with my advisor, Professor Franceso Bosello examines the determinants of climate related disasters and attempts to estimate the presence of adaptive capacity in terms of per capita income and population density elasticities. We provide empirical evidence that countries are able improve their adaptive capacity over the long run but also of some maladaptation occurring in the short run. Furthermore, using segmented regression analysis we find that higher income countries show adaptive capacity in a strong form, i.e. damages decrease with GDP but lower income countries highlight exactly the opposite behaviour. Finally, using Granger causality tests for panel data, we find evidence that increases in GDP per capita Granger causes climate related damages for lower income countries but not in higher income countries.

Acknowledgement

I am extremely grateful to my advisor and mentor - Professor Francesco Bosello for his guidance, advice, sharing his vast knowledge, and for his constant support during the course of my PhD. I feel privileged to have been able to work under him. His insights and feedback have greatly enhanced my work, thought-process, and have made me a better researcher.

I would also like to thank my co-tutor Professor Carlo Carraro for his support and helpful comments on my dissertation.

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Chapter 1

The Health Burden of Climate Change in US: Evidence from Influenza-Like Illness

Abstract

We find robust non-linear effects of both temperature and specific humidity on influenza mortality rates in the U.S. Using weekly data at the city level, we utilize Generalized Additive Models to investigate the relationship between climatic variables and influenza mortality rates in 122 cities during 1970 - 2010. Our results provide empirical support to epidemiological experiments under laboratory conditions stating that the highest risk of influenza is at extreme low and high temperatures ranges and at specific humidity levels between 4 g/kg and 12 g/kg (equivalent to Relative Humidity of 23% and 70%). The smoothed splines from our non-parametric analysis also demonstrate that the risk of influenza mortality is only positive at certain ranges of temperature and humidity. We also provide projections of influenza mortality for the U.S. under RCP 4.5 and RCP 8.5 scenarios and find that the West, Midwest, and the Southeastern parts of the country will be at high risk of influenza mortality by the end of the 21^{st} century - with mortality increasing by up to 3% in some areas.

Keywords: Climate change, Influenza Mortality, Temperature, Specific Humidity, Generalized Additive Model.

Preliminary draft: Please do not quote.

1.1 Introduction

Each year approximately 5 to 20 percent of U.S. residents suffer from influenza while more than 200,000 are hospitalized (CDC, 2014). The effect of influenza on the US health care system is substantial; 3.1 million hospitalized days and 31.4 million outpatient visits resulting in direct medical costs estimated at over $10 billion (Molinari, 2007). The influence of weather and climate on Influenza-Like-Illness (ILI) transmission and mortality has been studied in a variety of ways and with varying levels of complexity. However, the spatial and temporal coverage of the existing literature is limited and our current understanding of the mechanism is limited to laboratory based studies (Lowen, et al., 2007; 2008) and a few empirical studies focused on particular cities or regions. As a result the effect of temperature and humidity on influenza mortality remains disputed.

Exposure to extreme temperatures and/or humidity levels increases the risk of mortality mainly through impacts on our cardiovascular and respiratory systems. A number of studies (Deschenes and Moretti, 2007; Lowen, 2007; and Barreca and Shimshack, 2012) state that colder temperatures have greater influence on mortality than warmer temperatures but hot temperatures may affect the inter-temporal distribution of mortality by expediting the time-to-death of individuals already nearing death. Low humidity levels can lead to dehydration and increase the spread of influenza (Lowen et al., 2007; Xie et al., 2007; and Shaman and Kohn, 2009), while high humidity levels increases the effects of heat stress by impairing the body's ability to sweat and cool itself (Ahrens, 2009). Furthermore, low humidity conditions, which are often accompanied by low temperatures, enhance survival times of viral aerosols (Harper, 1961 and Schaffer, 1976). Many of the previous empirical studies on the impact of climate exposure and influenza related mortality (Braga et al., 2002; Schwartz et al., 2004 and Barreca and Shimshack, 2012) use simplistic linear models, while papers using more complex methodologies have focused on specific cities and regions and are mostly time series in nature (Murray and Morse, 2011; Shaman et al., 2010; and Soebiyanto et. al, 2014) to study these relationships. Another criticism of the existing literature is the extensive use of Absolute Humidity (AH) and Relative Humidity (RH) as covariates, these measure of humidity are dependent on temperature and as a result provided inconsistent and biased results (Weber and Stilianakis, 2008; Shaman and Kohn, 2009; and McDevitt et al., 2010). Our understanding of this relationship is also limited to *a priori* assumptions regarding the pre-determined knots of the exposure variables' distributions.

In this paper, we utilize a city-by-week level dataset over a span of 40 years for 122 cities in the U.S. - significantly larger than those used in the existing literature. The weekly influenza mortality data comes from the Centers for Disease Control and Prevention's (CDC) Morbidity and Mortality Weekly Report (MMWR). These observations were matched to temperature and specific humidity [1] data from the Global Land Data Assimilation System (GLDAS) forcing files. Combining these datasets we use Generalized Additive Models (GAM) with smoothing functions to investigate the impact of changes in these variables on influenza mortality rates. We find robust non-linear effects of both temperature and specific humidity on influenza related mortality rates and provide empirical evidence for epidemiological theories that the chances of deaths due to influenza are highest at the extremes ranges of temperature and at specific humidity levels between 4 g/kg and 12 g/kg. Finally, in order to determine the future impact of climate change on influenza mortality, we simulated the

[1] The climatic exposure variables of interest are near surface temperature (K) and near-surface specific humidity (g/kg).

predicted changes in temperatures and specific humidity for two time epochs of the 21st century (2026-2045 and 2081-2100) relative to a twenty-five year period of our analysis (1980-2005) [2]. Our projections show that the West, Midwest, and the Southeastern parts of the U.S. are at highest risk of increase in influenza mortality by the end of the century.

1.2 Climatic Variables and Influenza Interaction

The role of weather and climate in epidemiology and transmission of disease has been studied in a variety of ways and with varying complexity. The Fourth Assessment Report of the Intergovernmental Panel on Climate Change and Confalonieri et al. (2007) provides a comprehensive conceptual model including environmental, social, economic, and health care system conditions and the direct and indirect effects they have on human health. Epidemiological studies (Deschenes and Moretti, 2007; Lowens, 2007; and Barreca and Shimshack, 2012) state that colder temperatures have greater influence on mortality than warmer temperatures but hot temperatures may affect the inter-temporal distribution of mortality by shortening the time-to-death of already vulnerable individuals.

Declining and low temperatures are usually associated with increased seasonal influenza virus infection rates (Cox and Subbarao, 1999) and this association has been cited extensively to explain the decreased effect of seasonality in the tropics (Shih et al., 2005). However, Dowell and Ho (2004) questioned this association, stating that no direct biological relationship exists and cannot be an adequate explanation of seasonality.

Based on laboratory controlled experiments on guinea pigs, Lowen et al. (2007) demonstrate that low temperatures enhance viral stability. Examining the effect of temperature and relative humidity (RH) on aerosol transmission among guinea pigs, the authors find that peak viral shedding lasted 40 hours longer for guinea pigs housed at 5℃ relative to those exposed to 20℃. Furthermore, transmission among guinea pigs was inversely related to RH, with high rates of transmission at around RH of 20-35% but completely absent at RH of 80%. In this connection, Polozov et al. (2008) showed that the stability of the virus is highly dependent on temperature. Humidity can also affect human health through a variety of mechanisms. On one hand, low humidity levels can lead to dehydration and increase the spread of influenza (Lowen et al., 2007; Shaman and Kohn, 2009; and Xie et al., 2007). On the other hand, high humidity levels significantly worsen the effects of heat stress by impairing the body's ability to regulate its temperature (Ahrens, 2009). High humidity levels can also affect respiratory health as they promote the spread of bacteria, fungi, and dust mites (Baughman and Arens, 1996). These relationships suggest that indoor winter heating without humidification could enhance influenza transmission (Lowen et al., 2008), as indoor absolute humidity tends to be correlated with outdoor values and is typically lower in winter (Shaman et al., 2008). However, there is no robust empirical evidence of humidity and influenza mortality relationship, for example, Soebiyanto et al (2014) found positive association of humidity with influenza mortality in El Salvador and Panama but negative association in Guatemala.

McDevitt et al. (2010) showed that influenza survival is inversely related to absolute humidity. However, findings on the relationship between influenza transmission and RH were less consistent

[2] These data were generated by three General Circulation Models (GCM).

(Weber and Stilianakis, 2008). Some studies also found that aerosolized virus survival decreased as RH increased, while others showed a bi-modal relationship. Shaman and Kohn (2009) argued that absolute humidity (AH) influenced influenza virus survival and transmission efficiency more significantly than RH. Studies on temperate and tropical climates have demonstrated that low temperature (Tsuchihashi et al., 2011) and low humidity increase the risk of seasonal influenza onset in the winter (Murray and Morse, 2011; Shaman et al., 2010; and Shoji et al., 2011). Low temperature and dry air is also reported to increase influenza and pneumonia mortality (Davis et al., 2012). Furthermore, Shaman et al. (2010) found a consistent relationship between AH and virus survival in the US with extremely low AH conditions cause onsets of influenza with a 2 weeks lag. However, as mentioned earlier temperature and AH are strongly correlated, which could confound this result.

The actual causes could be among those already discussed, such as decreasing temperature resulting in increased indoor crowding (Lofgren, 2007). Decreases in ambient temperature may also result in increased physiological stress and energy costs for thermoregulation. This paper contributes to the debate by utilizing a non-parametric approach on a high resolution weekly dataset to determine the relationship between climatic variables and influenza mortality rate in the US.

1.3 Data and Variables

1.3.1 Global Land Data Assimilation System (GLDAS-2)

The climatic data for this paper comes from the GLDAS version 2. The goal of GLDAS is to ingest satellite and ground-based observational data products, using advanced land surface modelling and data assimilation techniques to generate optimal fields of land surface states and fluxes (Rodell et al., 2004). GLDAS drives four land surface models and integrates a huge quantity of observation based data and executes globally at high resolutions (2.5° to 1 km) enabled by the Land Information System (LIS) (Kumar et al., 2006). To obtain the weekly data, we averaged the pixels and aggregated the 3-hourly data into daily data and then computed the weekly maximum, minimum, and mean.

We use specific humidity is used since relative humidity is mechanically determined by temperature and the air's saturation point - the denominator to estimate relative humidity, and is positively related to the temperature. Thus, measurement error in temperature readings will be negatively correlated with measurement error in relative humidity. This measurement could bias the estimated effects of temperature and relative humidity. The corresponding data for the relevant cities were extracted in R using spatial coordinates for the 122 cities for which MMWR data is available.

1.3.2 Morbidity and Mortality Weekly Report (MMWR)

The dependent variable used in this paper, weekly influenza mortality was taken from the Morbidity and Mortality Weekly Report (MMWR). It is the weekly epidemiological digest for the United States published by the Centers for Disease Control and Prevention (CDC) and collects data from 122 cities and Metropolitan Statistical Areas (MSA) in the US within 2-3 weeks from the date of death.

1.4 Methodology

1.4.1 Generalized Additive Model (GAM)

We utilize generalized additive models (GAM) which includes a link function $g(.)$ relating the mean μ to the linear predictor $X\beta$. The general form can be written as;

$$g(\mu) = X\beta \tag{1.1}$$

Essentially, GAM is a non-parametric extension of Generalized Linear Models (GLM), used often for the case when there is no *a priori* reason for choosing a particular response function and the response functions needs to be generated from the data itself. GAMs are semi-parametric extensions of GLMs (Hastie and Tibshirani 1986; 1990); the only underlying assumption made is that the functions are additive and that the components are smooth. A GAM, similar to a GLM, uses a link function to establish a relationship between the mean of the response variable and a *smoothed* function of the explanatory variable(s). A GAM function with time and location fixed effects can be written as;

$$\gamma_{iwy} = \alpha_i + \phi_{wy} + \sum_{i=1}^{n} f_{iwy}(X_{iwy}) \tag{1.2}$$

The usual linear function of a covariate, $\beta_i.X_i$, is replaced with f_i, an unspecified smooth function. In Equation 1.2, α location fixed effects for the cities while ϕ is a set of year-by-week fixed effects included to control for the unobserved heterogeneity. We used *thin-plate* cubic spline smoothing functions for the exposure variables and the income variable. The idea behind using smooth functions is to remove the small variations while maintaining the major trend of each variable with a view to increase the efficiency in estimating the model. The non-parametric nature of GAMs mean that we do not need to assume a rigid form for the dependence of the response variable on the predictors. Another strength of GAM is their ability to deal with highly non-linear and non-monotonic relationships between the response and a set of explanatory variables. GAMs are sometimes referred to as data rather than model-driven. This is because relationship between the dependent and the predictors are determined by the data instead of assuming a form of parametric relationship (Yee and Mitchell, 1991).

Minimizing residual deviance while maximizing lowest possible degrees of freedom is the main statistical issue with GAM. Since GAM model fit is based on deviance, these fitted models are directly comparable to GLMs using likelihood techniques or classical tests based on model deviance such as Chi-squared or F-tests. One particular reason for GAMs being less frequently used than GLMs the difficulty of interpreting the results as no parameter values cannot be obtained. However, they are remain an extremely useful tool for prediction and interpolation and to explore the functional nature of a response (Hastie and Tibshirani, 1990 and Wood, 2006). In summary, GAMs are a compromise between ease of interpretation of linear models and the flexibility of general non-parametric models, this allows complicated non-linearity problems to be easily incorporated, even with many independent variables. This paper uses cubic splines to investigate the non-linear effects of temperature and specific humidity on influenza related mortality. We used the MGCV package (Wood, 2011) in R for our estimations.

1.4.2 Projections

In order to understand the impact of climate change on future influenza mortality, we use future climate projections data from three GCMs and combine them with our GAM estimates. We project the past climate using simulated historical weather from the GCMs for the years 1980 - 2005. One of the main reason for this strategy is that the observations of actual weather and mortality are on a different geography scale than the ones on which we ideally conduct the projections. Our econometric analysis has been conducted on the city level but GCM data are available for the U.S. at the county level only. The secondary reason for this approach is as important - bias correction. It is well known that GCMs do not correctly simulate weather over the historical period at high frequency. however, they estimate the average correctly over a longer time interval. Thus, juxtaposing the GCM projections of the future with observations of the past should provide unbiased comparisons. The remedy in this case is to compare each GCMs' projections of the future against its own simulation of the historical period and the resulting comparison will likely be bias free. We use data from three GCMs; GISS-ER-2 [3], CNRM-CM5 (Voldoire et al., 2015), and NorESM1-M (Bentsen et al., 2013 and Iversen et al., 2013) under 4.5 and 8.5 RCPs for the periods 2026 - 2045 and 2081 - 2100.

To operationalize this; we create a synthetic historical series by forcing the econometric estimates from the GAM analysis on the GCM simulations of the historical period. For these three periods, we computed the weekly temperature and specific humidity from the 3-hourly data generated by the GCMs and then estimated the influenza mortality for each period for each county in the U.S. Finally, we computed the climate-induced change in temperature and humidity exposure as the differences in these vectors of proportions between the future periods and the historical period to compute the difference in influenza mortality.

1.5 Results and Discussion

GAM generates response functions from the data itself and replaces the parameter values produced by OLS regressions with a cubic spline smoother for each predictor. These splines allow us to evaluate the relationship between the predictors with the residualized dependent variable values. We use the Maximum Likelihood (ML) estimation method in our analysis due to its stable covariance structure and the fact that it does not tend to under-smooth the data as is usually the case with the GAM Computation Vehicle (GCV) method (Wood, 2006). Both time fixed effects (year and week) and location fixed-effects (city) are included; thus we are measuring the excess mortality above the all-city long-run average rate for each week. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) tests suggest that specifications with contemporaneous temperature and humidity only are most robust (Table (A) of Appendix A), this shows that gestation periods for influenza viruses are rather short and that the infection period is rather short. [4].

Results from the minimum temperature and minimum specific humidity specification. Zhang et al. (2015) and Imai et al. (2014) both state that minimum specifications provide better fit, while Shaman et al. (2010), while Jaakkola et al. (2013) and Tsuchihashi et al. (2012) concluded that minimum temperature and minimum humidity are the major drivers of influenza. Figure 1.1.a

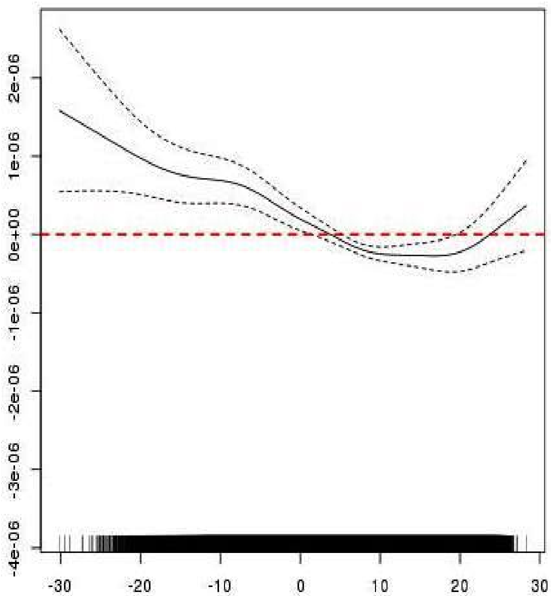
[3] `http://data.giss.nasa.gov/modelE/`

[4] The CDC states that adults may be contagious 1 day before influenza symptoms develop and up to 5 to 7 days afterwards

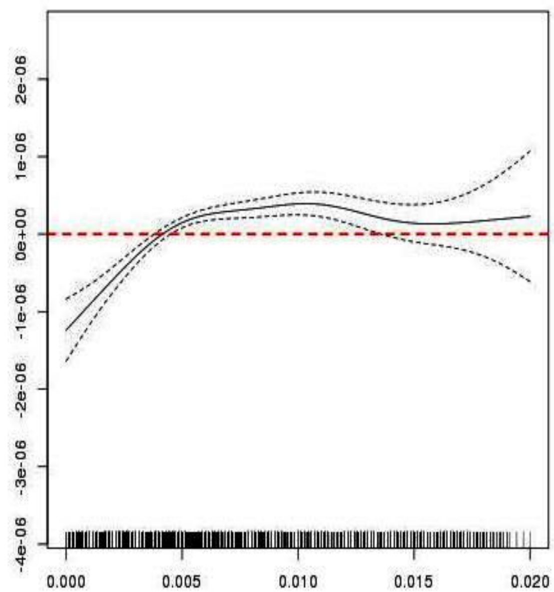
shows the spline of minimum temperature, the shape of the response function suggests that the risk of influenza mortality is highest at low temperature levels and that this risk is positive between -30℃ and 5℃. The risk is negative between 5℃ and 25℃, however, an *u-pattern* is evident as the risk again becomes positive beyond 25℃ - suggesting that the effect of temperature on influenza mortality is non-linear. The spline also suggests that the risk of mortality declines until 5℃, remains constant between 5℃ and 20℃ but increases beyond this point, thus any increase in temperature beyond 20℃ increases the risk of influenza mortality. Under laboratory conditions, Lowen et al. (2007 and 2008) demonstrated that viral shedding in animals is increased at 5℃, while others have noted that low temperatures reduce blood flow and that inhalation of cold air may increase susceptibility (Eccles, 2002 and Mourtzoukou and Falagas, 2007). Our results are consistent with these papers but our finding differs from the that of Barreca and Shimshack (2012) in that they find no significant relationship between low levels of temperature and monthly influenza mortality. However, this particular paper uses OLS regression techniques based on pre-determined knots of temperature and humidity to study this relationship.

The specific humidity spline in Figure 1.1.b suggests that the effect of humidity is negative below levels of 4 g/kg but influenza related mortality increases as humidity increases below this level. However, beyond this level, the risk of influenza mortality is positive and is highest at 12 g/kg. In perspective, our results suggest that at minimum specific humidity levels between 4 g/kg and 14 g/kg - influenza mortality is likely to increase. This finding is consistent with epidemiological literature stating that low levels of humidity significantly impacts influenza mortality (Polozov et al., 2007 and Lowen et al., 2008). While laboratory experiments by Lowen et al. (2007) also show that the efficiency of influenza viruses to be highest between RH of 20% and 35%; equivalent to specific humidity of 3.5 g/kg and 6 g/kg. It is also evident from our finding that the impact of humidity on influenza mortality is also non-linear. The medical and the epidemiological literature suggests that dry conditions result in moisture losses and lead to dehydration thereby increasing the spread of influenza through; greater viral shedding (Harper, 1961 and Schaffer, 1976), while results from animal studies indicate that low humidity increases the duration of the virus's reproduction in infected organisms, increasing virus stability in the environment and increasing the probability of transmission through coughing and sneezing (Lowen et al, 2007 and Noti et al., 2013). Yang et al. (2012) state that the viability of the influenza A virus is highest when Relative Humidity (RH) is below 50 percent, equivalent to a specific humidity level of 8.66 g/kg - within the range that we find risk of influenza mortality to be highest.

We also control for the annual income per capita for each city's corresponding MSA, the smoothed spline of this variable generally follows a declining pattern - suggesting that the risk of influenza mortality decreases as income per capita increases.



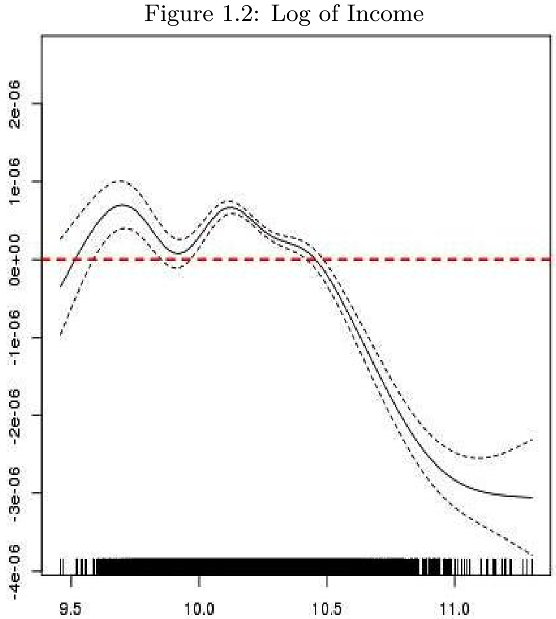
(a) Figure 1.a: Minimum Temperature



(b) Figure 1.b: Minimum Humidity

Figure 1.1: GAM Splines - Minimum Temperature and Minimum Humidity

Figure 1.2: Log of Income



In summary, our findings provide robust evidence that the effect of temperature and specific humidity on influenza mortality in the U.S. is non-linear. The risk of influenza mortality is highest at extremely low levels of temperature (-30°C). This risk is positive until 5°C and again beyond 25°C. As for specific humidity, the risk of mortality is between 4 g/kg and 12 g/kg but negative below 4 g/kg, although the spline suggests that any increase in humidity below 4 g/kg increases the risk of influenza mortality.

1.5.1 Sensitivity Analysis

The splines for the maximum and the mean specifications are provided in Appendix A. The spline for maximum temperature in Figure A.1.a suggests that the risk of influenza mortality is highest at low levels of temperatures(around -20°C) but this risk is negative beyond maximum temperature levels of 20°C. As for maximum humidity (Figure A.1.b), the risk is positive between maximum humidity levels of 16 g/kg and 26 g/kg and highest at 22 g/kg. The mean temperature spline (Figure A.2.a)suggests that influenza mortality risk is positive between mean temperature levels of -30°C and 15°C, while the mean humidity spline (Figure A.2.b) shows that this risk is positive between mean humidity levels of 6 g/kg and 22 g/kg and the risk is highest at 16 g/kg.

In order to test the robustness of our results, we tried a number of different specifications. We find that data truncated for the influenza season has no effect on the shape of the response functions, neither does including a cyclical smooth term to control for the seasonality of influenza. Since spatial serial-dependence can be an issue with GAM, we included a bi-variate smoothing spline with latitude and longitude of each city but the response functions generated are not different from our preferred specification. Furthermore, influenza mortality is unaffected by the inclusion of lags of dependent and/or independent variables, the fit of the models do not improve and the splines of temperature and specific humidity do not seem to change.

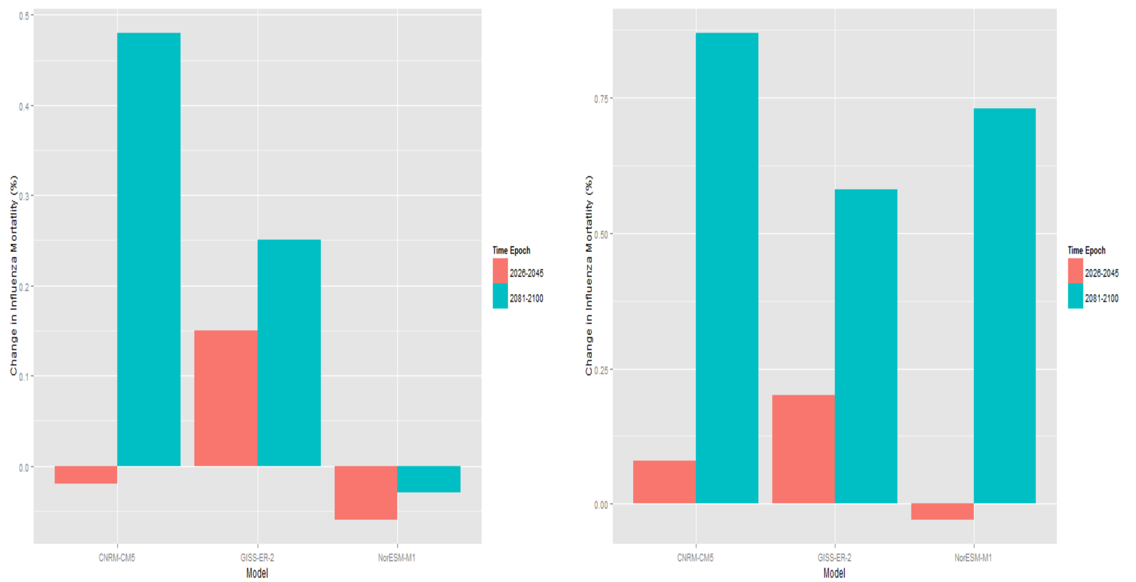
1.5.2 Projections

We estimate the projected changes in influenza related mortality due to effects of climate change on temperature and humidity in 3109 counties in the U.S. The changes in mortality rates were computed by combining the GAM estimates in Figure 1.1 with changes in weekly temperature and humidity projected by three GCMs. First, we calculated the fitted values at each year-by-week observation and collapsed the predictions by FIPS code. Then, we summed over weeks to obtain annual per capita mortality and averaged over all the historical years. Secondly, for future periods simulated by the GCMs, we followed the exact same procedure as for the historical period, above. Computing the difference between these two periods - provides the projected change in influenza related mortality due to climate change.

Our projections of the changes in influenza related mortality suggests that under the RCP 4.5 scenario and during the mid-century; the largest possible decline will be -3.7% while the largest possible increase is projected to be 4.8%. Under the same scenario but for the end of the 21st century, the highest decline in mortality rates is projected to be -3.2% while the highest increase will be 4.7%. Under the RCP 8.5 scenario in the mid-century, the highest decline and increase are projected to be -3.5% and 5%, respectively. While the same changes are projected to be -3.4%

Figure 1.3: Mean Projected Changes in Influenza Mortality (%)

(a) Figure 2.a: Change in Influenza Mortality - RCP: 4.5 (b) Figure 2.b: Change in Influenza Mortality - RCP: 8.5



and 4.9% during the end-century, respectively. The mean estimates of the three GCMs are provided in Figure 1.3.

Under RCP 4.5, the mean change in climate change induced mortality across the U.S. in the mid-century is expected to be small; ranging from -0.02% to 0.28%. The changes at the end-century for the same scenario is projected to be slightly higher between -0.03% and 0.48%, depending on the GCM. While for the 8.5 scenario, the mean changes range from -0.03% to 0.31% at mid-century to 0.58% to 0.87% at the end of the century. As demonstrated in Figure A.3 in Appendix A, parts of West and Southwest U.S. are likely to experience increases (0.60% to 1%) in influenza mortality during the mid-century under the RCP 4.5 scenario, the climate in the Western U.S. is usually semiarid with extreme temperatures over the summer and winter along with low levels of humidity (Arizona and New Mexico). These climate and weather patterns means that these regions are conducive to influenza. The Northwest and Midwest U.S. are likely to have declines in influenza mortality (-0.20% to -0.40%). Projections under the same scenario for the end of the 21st century (Figure A.4) suggests that the Mid-west, Southeast, and Northeaster parts of the U.S. will likely experience increases in influenza mortality (0.50% to 1.5%). The Midwestern states have humidity levels within around 10 g/kg (equivalent to RH of 57%), while some parts of the Southeastern states (Georgia and Florida) often experience temperatures above 25°C.

Projections of influenza mortality during the mid-century using the RCP 8.5 scenario (Figure A.5), suggests that the Southwest, Midwest, and Southeastern parts of the U.S. will experience small increases in influenza mortality (0.20% to 0.60%). As described above, the humidity and temperature interaction in these regions are the likely causes driving the increase. As for the end-century under this scenario (Figure A.6), the Southeast (North Carolina, South Carolina, Georgia, and Florida), the Midwest (Nebraska, Illinois, and Kansas) and some parts of the Eastern U.S. (Massachusetts and Rhode Island) will experience relatively large increases in influenza related mortality (up to 3%) [5].

Our projections on the impact of climate change on influenza mortality by the end of this century suggests that the West, Midwest, and the Southeastern parts of the U.S. will likely face increases in influenza mortality. Furthermore, there seems to be a spatial shift of influenza mortality from the West/Southwestern to the South/Southeastern U.S. during the 21st century. We provide the projections with the usual caveat that the climate projections from the GCMs are produced with various degrees of uncertainty - we have tried to address this particular issue by using a bias-correction methodology described in the 1.4 section. Another issue is that the change in vaccination among the U.S. population and the variations in influenza strains that cannot be controlled for.

1.6 Conclusion

In this paper, we provide robust evidence that the effects of both temperature and humidity on influenza mortality rates are non-linear. We find that the risk of influenza mortality is positive only at certain ranges of temperature; between -30°C and 5°C but the spline has a declining shape and the risk becomes negative between temperature range of 5°C and 25°C. However, the risk of mortality become positive again as temperature increases beyond 25°C. This particular finding provides evidence that the risk influenza related mortality is most sensitive at the extreme levels of temperature. The effect of humidity is highest between specific humidity levels of 4 g/kg and 12 g/kg. Our results also suggest that influenza mortality is insensitive to lagged weekly temperature and humidity. The findings are consistent with the existing literature and provide comprehensive empirical evidence to a number of influential epidemiological works under laboratory condition by Cannell et al. (2008), Lofgren et al.(2007) and Lowen et al. (2007; 2008). It may be that ambient temperature is simply strongly correlated with the actual mechanism responsible for driving seasonality and these actual causes could be among those already discussed including the fact that decrease in temperature induces behavioural changes such as increased crowding. Decrease in temperature also results in increased stress and energy costs, which could weaken the immune system and increase susceptibility and as stated in the existing literature, viral particles have a longer survival rate in colder temperatures (Lofgren, 2007). Low humidity increases the virus stability and transmission rates (Lofgren et al., 2007 and Jaakkola et al., 2014) while high humidity levels can affect respiratory health since they promote the spread of bacteria, fungi, and dust mites and by impairing body's ability to regulate its own temperatures (Baughman and Arens, 1996).

Finally, our projections on the expected impact of climate change on influenza mortality suggests that the West, Midwest, and the Southeastern parts of the U.S. are at high risk of influenza mortality increase in the coming century (up to 3% in some areas). Furthermore, there seems to be a spatial shift of influenza mortality from the West and Southwestern parts of the U.S. to the South

[5] The regional climatic patterns were taken from the USGS Climate Maps

and Southeastern regions during the 21st century. Thus, the distribution of the future changes in influenza will be unequal across the U.S. These findings can be used to target locations at high risk of influenza mortality and the non-linear estimations means that vaccination drives can be focused at specific times and the projections can be used to target the particularly vulnerable regions.

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Chapter 2

Impact of Climate Change on Malaria: A Quantile Regression Analysis

Abstract

The number of deaths from malaria in the world was estimated to be more than 1.2 million in 2010 while there were 216 million cases of malaria in Africa alone. The impacts of climate changes are increasingly evident through movements of climatic variable such as temperature and precipitation on different time scales. Using an updated global malaria mortality dataset for 105 countries between 1980 and 2010 and utilizing a quantile regression framework, this paper finds that the optimal temperature for countries with relatively low malaria mortality rates is 32.6°C; slightly higher than previous estimates. However, the optimal temperature for countries with relatively high malaria mortality is estimated to be 24.07°C; lower than that suggested recently by Mordecai et al. (2013) but between 5°C - 6°C lower than other estimates. This is one of the first papers to provide global scale empirical evidence that the effect of temperature and precipitation on malaria mortality is non-linear. These estimates can be used to understand the impact of future changes of temperature and precipitation on malaria mortality. This can be used to target vulnerable regions near the threshold of optimal temperature and precipitation levels for malaria mortality and can be an important tool to identify areas at risk of increase in malaria.

Keywords: Climate change, Malaria, Vector borne disease, Temperature, Precipitation, Quantile Regression.

Preliminary draft: Please do not quote.

2.1 Introduction

Vector-borne diseases (VBD) are infections transmitted by the bite of infected arthropod species, such as mosquitoes, ticks, triatomine bugs, sandflies and blackflies. These are among the major microbial causes of morbidity and mortality in the world today affecting nearly half of the world's population, the majority of who reside in developing countries located in the tropical and subtropical climate (WHO, 2009). Changes in climatic variables have significantly altered the distribution of some infectious disease vectors. IPCC specifically mentions malaria, dengue, yellow fever, leishmaniasis, and cholera as the vector-borne diseases that are most likely to be affected by the changing climatic conditions (IPCC, 2007). Among these diseases; malaria is considered to be the most sensitive to changing environmental conditions (Martens et al., 1998; Martens et al., 1999; and Rogers and Randolph, 2000).

The balance between temperature and precipitation is critical for breeding and transmission of malaria vectors and hence for the transmission of malaria. It is also the most deadly and widespread. In 2014, 97 countries and territories had malaria transmission while an estimated 1.2 billion people were at high risk [1]. In the high-risk areas, the rate of malaria transmission is more than one per 1,000 of population. Malaria is one of the most widely transmitted vector-borne diseases around the world and according to the World Health Organization (WHO); death burden of malaria has increased over the last decade (WHO, 2010a). The number of deaths from malaria in the world was estimated to be more than 1.2 million in 2010 while there were 216 million cases of malaria in Africa alone (WHO, 2010b and Murray et al., 2012). While the fact that climatic variables affect malaria transmission is known (Alonso et al., 2011), the mechanism of the impact of climate change on malaria deaths is less clear.

In this paper, we utilize an annual global dataset over a span of 30 years, larger than those used in the current empirical literature. The climatic data for this paper comes from the Global Historical Climatology Network (GHCN) version 2 (precipitation) and version 3 (temperature) while the data on malaria deaths comes from the Institute for Health Metrics and Evaluation (IHME). Combining these datasets we use quantile regression on panel data to investigate the impact of changes in climatic exposure variables on malaria deaths in 105 countries [2] during 1980 - 2010. We provide one of the first empirical evidence on the effect of temperature and precipitation on malaria mortality on a global scale. We find that the optimal temperature for countries with high malaria mortality rate is lower than previously thought. While the optimal precipitation level is also estimated to be lower than the 80 mm per month suggested in the existing literature. Our results confirm the non-linear nature of the relationship between the climatic exposure variables and malaria mortality and can be used to predict the impact of future changes of temperature and precipitation on malaria mortality.

[1] Population at risk (High + Low): High = population living in areas (reported malaria incidence $>$ 1 per 1000/year) defined at administrative level 2 or lower. Low = population living in areas (reported malaria incidence $<$ 1 per 1000/year)

[2] List of countries is provided in Table B.1

2.2 Determinants of Malaria Transmission

Changes in temperature influence the incubation period of malaria parasites and hence influence malaria transmission rates. Temperature also affects the lifespan, growth and biting rates of mosquitos (Lindsay et al., 1998; Craig et al., 1999; Grover-Kopec et al., 2005; and Gething et al., 2011). Rainfall often leads to stagnant water critical for breeding of mosquito eggs (Craig et al., 1999; Kiszewski et al., 2004; and Thomson et al., 2005). This makes malaria one of the most climate sensitive outcomes.

Three crucial elements coexist in order for VBDs such as malaria to occur; susceptible population, the vector (most often arthropods), and the disease pathogen (bacteria, virus, and parasite). Arthropods are rather sensitive to changes in temperature and precipitation as they are physiologically unable to regulate their temperatures and are therefore dependent on climate for survival and development (Githeko et al., 2000). Higher temperatures along with adequate rainfall are likely to aid the transmission procedure of vector-borne diseases. Mosquitoes carrying parasites transmit malaria and its distribution usually depends on the availability and productivity of breeding habitats. In most cases the breeding habitat is stagnant water, which remains after rainfall (Githeko, 2008). Indeed there are a number of areas in the world where conditions may be suitable for all three components; however, factors such improved health services or vector control measures have prevented or helped to eradicate disease transmission (Gubler et al., 2001 and Koenraadt et al., 2004). Nonetheless, proactive prevention and treatment actions are also determinants.

Ultimately, while the connection between the climatic variables and malaria is evident, the *ex post* impact of the changes in these variables on malaria mortality is less so. Some studies have reported that increase in global temperatures will likely lead to an increase in malaria cases (Martens et al., 1999 and Pascual et al., 2006) but Rogers and Randolph (2000) find no significant impact, while Gething et al. (2011) concluded that malaria rates will decline regardless of changes in temperature. The optimal temperature for malaria transmission has often been considered between 20℃ and 30℃ (Casman and Dowlatabadi, 2002 and Dasgupta et al., 2012) but Martens et al. (1998) stated it to be 31℃. Mordecai et al., (2013), using thermal response functions conclude that the optimal temperature for malaria transmission is much lower at 25℃. As for precipitation, it is regarded that the minimum rainfall required for breeding of malaria vectors is 80 mm per month (Ermert et al., 2013 and Caminade et al., 2014). This paper estimates the optimal points for both temperature and precipitation using quadratic regression functions and quantile regression to understand the impacts of these variables on the entire distribution of malaria mortality across countries and three decades.

2.3 Literature Review

The relationship linking climatic variables and transmission of vector-borne diseases has been studied in both the medical science and the health economics literature. Epidemiologists, using linear regression techniques argue that the relationship between temperature and malaria transmission is linear. Many papers including Anderson and May (1992), Lindsay et al. (1998) and Lafferty (2009), use standard epidemiological models to study the relationship between the vectors and pathogens of malaria and temperature to conclude that reproductive rate of malaria vectors increased between 0.5 and 4.0% as temperature increased.

A number of papers using biological models to estimate the effect of changing climatic variables on malaria also found similar results. Martens et al. (1999), controlling for vector specific information on the pathogens of malaria and dengue suggest that extreme temperature and periods of heat stress aid the reproduction and transmission rate of malaria. Chaves and Koenraadt (2010) used a similar model with data from four East African countries and found that an increase in number of heat days during a season has increased malaria outbreaks over the last three decades. A review of the medical science literature reveals that as water temperature rises, the maturity time for larvae decreases (Rueda, 1990) and consequently the reproduction rate increases during the transmission period. In warmer climates, adult female mosquitoes digest blood faster and feed more frequently (Gillies, 1953), thus increasing transmission intensity. Similarly, malaria parasites and viruses complete extrinsic incubation within the female mosquito in a shorter time as temperature rises (Turell, 1989), thus increasing the proportion of infective vectors. However, Gillies (1953) concluded that as the mean temperature increases above a certain threshold (approximately between 34℃ and 38℃) there is generally a negative impact on the survival of vectors and parasites.

The biological models have been criticized for not incorporating both the climatic variables simultaneously, as a result the estimation results from these models often suggest large increases in malaria transmission (Martens et al., 1998 and Rogers and Randolph, 2000) [3]. Standard statistical models that have been used as an alternative to study the major influencing factors of malaria transmissions also suggest that changes in climatic variables affect malaria transmission. Cox et al. (1999) use the number of reported cases in East Africa as a dependent variable and suggest that there is a positive relationship between rising temperature and the number of cases of malaria reported.

Mouchet et al. (1996) conclude that a decrease in rainfall in the Sahel Region of Africa results in a decline in the transmission rate of malaria vectors, while Thomson et al. (2005) controls for precipitation and sea-surface temperature in Botswana and find that the variability of the climatic variables can be used to explain nearly 70% of the variability in the reported malaria incidences. While Singh and Sharma (2002) suggest that decrease in rainfall in central India has negatively affected the productivity rate of larva responsible for malaria vectors and pathogens. However, most of these statistical models also suffer from missing variable bias, arising from the fact that almost none of them control for health expenditure. WHO has maintained that public health expenditure has helped to reduce the transmission rates and in some cases even to eradicate malaria transmission (WHO, 2009).

A common trait of the existing literature on the relationship between climate change and transmission of vector- borne diseases is to focus mainly on either individual countries (Githeko et al., 2000) or on specific sites within countries (Zhou et al., 2004). Moreover, it has mostly involved changes of only temperature in the models (Hoshen and Morse, 2004), despite the medical literature increasingly suggesting that both temperature and precipitation affect the transmission of malaria (Zhou et al., 2004). Accordingly, the differences in these results, to some extent, can be largely attributed to the different models of malaria transmission used and to the different locations and time scales of the particular studies (Lafferty, 2009; Paaijmans et al., 2010; Parham et al., 2010; Blanford et al., 2013; and Ermert et al., 2013). More recent studies have mostly focused on the

[3] This is a common issue across the existing literature.

modelling or mapping of malaria (Parham et al., 2012; Alonso et al., 2011; Ermert et al., 2013; and Sagara et al., 2014).

The literature studying the relationship between climatic variables and malaria transmission, along with suffering from model misspecification (e.g. assuming linear relationship of climatic variables) and missing variable bias (e.g. health expenditure), and mostly assume that this relationship is homogeneous across regions and countries. As evident from the review, very few papers (Paaijmans et al., 2010 and Caminade et al. 2014 being exceptions) have attempted to study the impact of climate exposure on malaria mortality; even these two papers use simulated models. This paper is one of the first to investigate the effects of changes in climatic variables on quantiles of the malaria mortality on a global scale using up-to-date mortality data. In this framework malaria mortality will be a function of the climatic exposure variables and public health expenditure as percentage of GDP. We have included country and year fixed effects to control for unobserved region-specific and time-invariant effects and relax the assumption that the impact of temperature and precipitation are homogeneous across countries (Koenker, 2004). We also contribute to the existing literature by estimating the optimal thresholds for both temperature and precipitation.

2.4 Data and Descriptive Statistics

The goal of the paper is to investigate the impact of climatic exposure variables of temperature and precipitation on malaria mortality using data from 105 countries between 1980 and 2010. The climatic data comes from the Global Historical Climatology Network (GHCN-M) version 2 for precipitation (Peterson and Vose, 1997) and version 3 for temperature (Lawrimore et al., 2011). It is an integrated dataset of temperature, precipitation, and pressure records managed by the National Climatic Data Center, Arizona State University, and the Carbon Dioxide Information Analysis Center (Menne et al., 2012). This dataset contains monthly mean temperature and precipitation data from across the world. The temperature data is collected by 7,280 stations while the precipitation data comes from 20,590 stations across the world. To obtain the annual means, we averaged the stations for each country and year.

The malaria data comes from IHME's publication in The Lancet global estimates for malaria mortality - Global malaria mortality between 1980 and 2010: a systematic analysis. The estimates are based on data from 105 countries from a total of 1,150 site years between 1980 and 2010. Data from vital registration systems and from verbal autopsy studies were used for these estimates. The study uses a number of predictive models to estimate the malaria mortality with uncertainty by age, sex, country, and year and includes critical predictors of malaria mortality such as *Plasmodium falciparum*, antimalarial drug resistance, and vector control and finally.

Table 2.1 below provides the descriptive statistics. The average annual temperature in the overall panel is 17.37 and the average precipitation is slightly less than 775 mm per year.

Table 2.1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
GDP per capita (PPP USD)	7,841.24	11,210.82	142.02	1.15 . 10^5
Health Expenditure/GDP (%)	5.5	2.04	0.81	16.79
Malaria Mortality (Rate per 100,000)	12,385.6	38,940.9	0	5.25 . 10^5
Population	4.27 . 10^7	1.53 . 10^8	92,160	1.34 . 10^9
Mean Temperature (℃)	17.37	11.8	-25.73	29.5
Mean Precipitation (mm)	774.33	97.62	0	964

The following figures show the classification (Figure 2.1) and percentage of population at risk of malaria by country (Figure 2.2). Figure 2.2 suggests that the high majority of malaria cases occur in Africa (90% according to some estimates).

Figure 2.1: Country Malaria Classification - 2014

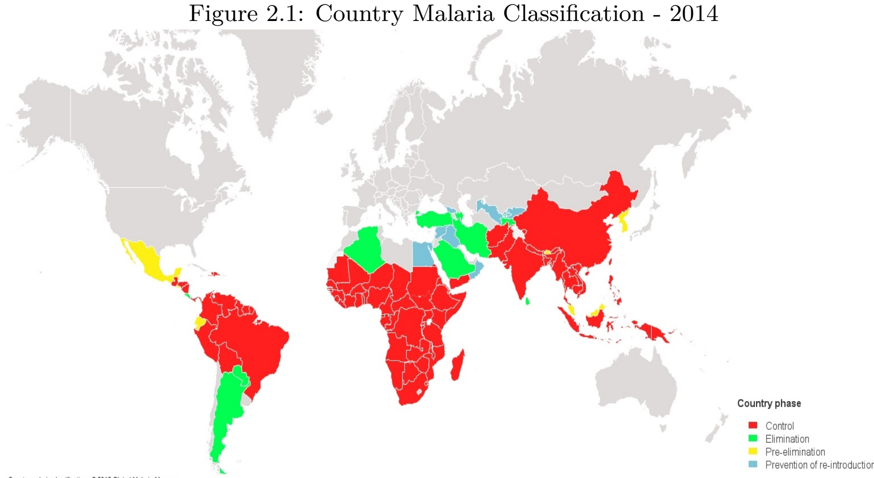
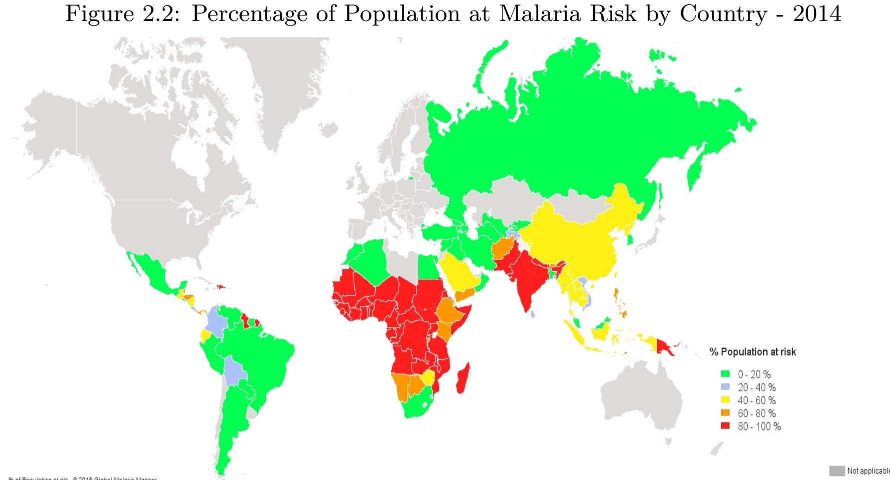


Figure 2.2: Percentage of Population at Malaria Risk by Country - 2014



The IPCC reports (2007 and 2014) mentions that vector control is the single most efficient method of controlling transmission of malaria and that changes in climatic patterns may have decreased the rate of decline in mortality caused by malaria and at the same time may increase the transmission rates in the years to come. This paper makes an attempt to study this particular linkage with respect to temperature and precipitation. According to the IHME study, global malaria deaths increased from 995,000 in 1980 to 1.8 million in 2004. Malaria mortality was estimated at 1.2 million in 2010 - a decrease of 32 percent over 2004. This particular decrease are likely driven by the pattern of malaria mortality in sub-Saharan Africa, where deaths increased to 1.6 million in 2004 (493,000 in 1980) but decreased to 1.1 million in 2010 - a decline of 30%. However, in the rest of world, there has been a constant decline in malaria mortality, from 502,000 in 1980 to 104,000 in 2010.

2.5 Methodology

In order to estimate the impact of changes in the climatic variables of temperature and precipitation on the mortality rate of malaria, we estimate the following reduced form model;

$$\gamma_{it} = \alpha_i + \phi_t + \beta_1 T_{it} + \beta_2 T_{it}^2 + \beta_3 P_{it} + \beta_4 P_{it}^2 + \beta_5 Exp_{it} + \epsilon_{it} \tag{2.1}$$

Where, γ_{it} is the natural log of population malaria mortality rate in country i in period t. The variable T_{it} represents annual mean of temperature while P_{it} is the annual mean for precipitation. Exp_{it} is the natural log of health care expenditure per capita and ϵ is the composite error term. While α represents country fixed effects and ϕ_{it} represents year fixed effects. Squared terms (T_{it}^2 and P_{it}^2) for both temperature and precipitation have been added as discussed in Section 2.2 and Section 2.3 - the relationship between the climatic variables and malaria mortality is either concave or convex, i.e. the relationship wears off at certain point or there is a minimum point after which the relationship becomes significant. Lagged term for health expenditure per capita has been used as the expenditure on vaccines and other services to reduce malaria in year *t-1* is likely to have an effect in year t at the earliest [4]. While it is more common to use Poisson regression in this type of studies in order to account for the fact that the reported number of cases can be zero, we chose to use log of malaria mortality to accommodate the quantile regression function. Furthermore, the data suggests that the zero mortality cases are mostly in countries that had no cases of malaria during 1980 - 2010.

Our model relies upon climatic variables; as such it suffers from particular limitations. For example it is difficult to accurately predict the impact of changes in temperature and precipitation on malaria in bordering regions/countries, especially those connected via water bodies. While some of the increases in malaria rates may be attributed to changes in characteristics of malaria vectors (due to drug resistance) and as a proxy for malaria eradication efforts, health expenditure data is used.

2.5.1 Quantile Regression

Quantile regression provides robust estimates in the presence of outliers, as is the case in malaria data. It also offers a method for inferring the conditional distribution of an outcome of interest over

[4] AIC and BIC test suggests that the optimal lag for health care expenditure is 1 year.

the entire support of its distribution, which allows us to examine the effect of covariates at different points on the distribution. For the 25th quantile regression (low malaria rates), the constant is the 25^{th} percentile for the sample of countries while for the 75^{th} quantile regression, the constant is the 75^{th} percentile of high mortality countries.

The classical form for linear regression (Li and Racine, 2007) can be written as;

$$\gamma_{it} = x'_{it}\beta + \alpha_i + \mu_{it}, i = 1, ...N, t = 1, ...T \tag{2.2}$$

Where γ_{it} is the dependent variable and $x_{it} = (1,\ x_{it},\ 2,\ .\ \ .\ \ .\ \ ,\ x_{it},\ p-1)'$ is a vector of independent variables, α_i are unobservable time-invariant fixed effects while μ_{it} represents the error term. We assume that the error term in Equation 2.2 has mean zero and is orthogonal to the independent variables, thus the conditional mean function can be written as;

$$E(\gamma_{it}|x_{it}, \alpha_i) = x'_{it} + \alpha_i \tag{2.3}$$

Where γ_{it} is the dependent variable, x_{it} is the vector of covariates, and α_i is an individual fixed effect. The quantile model form can be written as [5];

$$Q_{\gamma_{it}}(\tau_j|x_{it}, \alpha_i) = x'_{it}(\tau_j) + \alpha_i \tag{2.4}$$

Where τ represents quantiles and Equation 2.4 is for all quantiles in the interval (0, 1). The parameter $\beta(\tau_j)$ models the effect of the covariates x_{it} - this relationship varies based on the quantile τ, the α_i are location effects and do not change. Our estimation of $\beta(\tau_j)$ provides linear approximation for the entire conditional distribution of malaria rates given temperature, precipitation, and health expenditure.

In a linear regression, the regression coefficient represents the change in the response variable produced by a one-unit change in the predictor variable associated with that coefficient. The quantile regression parameter represents the effect of a one-unit change of the explanatory variables on the specified percentile of the outcome variable. This allows comparing how some quantiles of malaria mortality rates may be more affected by certain explanatory variables such as temperature and precipitation. If increases in temperature and precipitation mean have a greater effect on countries with already high malaria mortality, then there is a major cause for concern. The quantile regression model can be expressed as;

$$\gamma_{it} = \alpha_i + \phi_t + \beta_1 T_{it}^{(p)} + \beta_2 T_i^{2(p)} t + \beta_3 P_{it}^{(p)} + \beta_4 P_{it}^{2(p)} + \beta_5 Exp_{it}^{(p)} + \epsilon_{it}^{(p)} \tag{2.5}$$

Where 0 < p < 1 indicates the proportion of malaria rate below the percentile at p. The quantile function completely characterizes the distribution function of a random variable and makes it possible to estimate the country level features of the complete condition of the distribution of mortality rates. Another advantage of Quantile regression is that it allows for the country-specific heterogeneity (by including the fixed effects) and the heterogeneity of covariate effects (Koenker, 2004).

[5] Koenker and Bassett (1978)

Whereas the asymptotic theory for quantile regression estimators are well developed for cross-sectional data, combining quantile regression models in panel data framework, which controls for unobserved heterogeneity (fixed effects) becomes rather complicated. This is because quantile regression allows the covariates to vary based on unobserved proneness, which becomes observed when individual fixed effects are added to the model, thereby changing the interpretations of the covariates. Also, the typical approaches are used to difference out the fixed effects do not apply to quantile regression for panel data as the quantile of the difference are not usually equal to the difference in quantiles (Powell, 2008 and Ponomareva, 2011).

As inclusion of individual fixed effects often changes the interpretation of the coefficients of these variables, Koenker (2004) and Harding and Lamarche (2019) focused on treating the fixed effects in the context of a penalized estimator by separating the estimation of the fixed effects and the other covariates though an L2 penalty. However, since the L1 penalty [6] allows the shrinkage of the fixed effects, as a result decreasing the variability in the estimation of β it has been used in this paper. The quantile regression for panel data was carried out using the *Quantreg* package in R (Koenker, 2015).

2.6 Results and Discussion

The results from the first set of regressions are presented in Table 2.2; column 1 shows results from a simple OLS specification, column 2 provides results from a specification with robust standard errors while column 3 results have both country and time fixed effects along with robust standard errors. We find that the linear term for temperature is positive and significant at the 1% level (Table 2.2: Column 1) while the squared term for temperature is negatively significant. This suggests although the malaria mortality rate increases with mean temperature, as the mean temperature crosses a certain threshold, further increases in temperature starts to negatively impact the rate of malaria mortality. This finding is consistent with the existing biological literature (Detinova, 1962) and (Muir, 1982). The optimal temperature for malaria mortality is found to be 26℃ (Table 2.2); this figure is 1℃ higher than that of Mordecai et al. (2013).

[6] L1 and L2 penalized estimation methods shrink the estimates of the regression coefficients towards zero relative to the maximum likelihood estimates. The purpose of this shrinkage is to prevent over fit arising due to either collinearity of the covariates or high-dimensionality. Although both methods are shrinkage methods, the effects of L1 and L2 penalization are quite different in practice. Applying an L2 penalty tends to result in all small but non-zero regression coefficients, whereas applying an L1 penalty tends to result in many regression coefficients shrunk exactly to zero and a few other regression coefficients with comparatively little shrinkage (Goeman and Meijer, 2012).

Table 2.2: OLS Regression Results

Variables	**Malaria Mortality**		
Temperature	0.266***	0.266**	0.266***
	(-0.008)	(-0.005)	(-0.002)
Temperature squared	-0.005***	-0.005***	-0.005***
	(-0.001)	(-0.001)	(-0.001)
Precipitation	-98.24	-98.24	-98.27*
	-2.1	-1.32	(-0.72)
Precipitation squared	0.048	0.052	0.045*
	(-4.2)	(-3.6)	(-2.9)
Lagged Health Expenditure per capita	-0.518***	-0.518***	-0.704***
	(-0.042)	(-0.045)	(-0.031)
Constant	-11.47***	-11.63***	-12.960***
	-0.83	-0.84	-0.8
R^2	0.36	0.31	0.44
Observations	2,832	2,832	2,832
Fixed Effects	No	No	Yes
Number of Countries	105	105	105

Standard errors in parentheses
*** p>0.01, ** p>0.05, * p>0.1.

The above results suggest that countries experiencing temperature increases until 26.6℃ will have increased malaria mortality but the mortality is likely to decline beyond this point. The coefficients of linear precipitation terms are negative while the squared terms are positive, however, only the precipitation coefficients for the fixed-effects regression are statistically significant. This suggests that controlling for the county-specific characteristics and average differences across countries are critical in understanding the determinants of malaria mortality. The estimation suggests that the optimal level of precipitation is 1,092 mm per year for malaria vectors, this is slightly higher than optimal rainfall if 80 mm per month suggested in the medical literature. Results also show that increases in health expenditure have a negative impact on the rate of malaria mortality; all the coefficients for health expenditure are statistically significant at the 1% level. These results demonstrate that the effect of temperature and precipitation on malaria mortality is non-linear and that there is a bell-shaped relationship between these climatic variables and malaria mortality.

2.6.1 Quantile Regression Results

For both the 25^{th} (Table 2.3: column 1) and 75^{th} (Table 2.3: column 2) quantiles, we find that the linear coefficients for mean temperature are positive and statistically significant. The linear terms for precipitation for both quantiles are negative and statistically significant. Squared temperature terms are negative while the squared precipitation terms are positive for both the quantiles. These results suggest that the optimal temperature for the 25^{th} quantile (countries with relatively low malaria mortality) is 32.6℃; higher than that suggested in the existing literature. The optimal temperature estimated for the 75^{th} quantile (countries with relatively high malaria mortality) is 24.07℃, slightly lower than 25℃ suggested by Mordecai et al. (2013) but closer to the range of 24.2℃ and 25.2℃ suggested by Huey and Berrigan (2001). As the mean temperature increases beyond these thresholds, further increase in temperature is likely to result in a decline in malaria mortality. The squared terms for precipitation are positive for both quantiles, suggesting a concave shape of the response function. In the year 2010 (the last year for which malaria data is available), 20 countries (37% of countries with high malaria mortality) had a mean temperature below 24.07℃.

Table 2.3: Quantile Regression Results

	Dependent Variable: Malaria Mortality	
	(25^{th} Quantile)	(75^{th} Quantile)
Temperature	0.326*	0.337***
	(-0.144)	(-0.007)
Temperature squared	-0.005*	-0.007***
	(-0.003)	(-0.001)
Precipitation	-98.8	-95.3***
	(-2.085)	(-0.158)
Precipitation squared	0.044*	0.051***
	(-6.211)	(-0.369)
Log of Health Expenditure/capita	-0.49***	-0.399**
	(-0.01)	(-0.103)
Constant	-15.78***	-15.16***
	(-1.062)	(-1.605)
Pseudo R2	0.49	0.56
Observations	2832	2832

Standard errors in parentheses
*** p>0.01, ** p>0.05, * p>0.1.

The estimated optimal precipitation for the 25^{th} quantile is 1122.73 mm per year, however, the coefficient is not statistically significant. For the 75^{th} quantile, the turning point is estimated at 934.3 mm per year, this value is slightly lower than the 80 mm per month suggested in the existing literature but well within the confidence interval. In 2010, 66 countries in our dataset had a mean precipitation level above this threshold. This is a cause of concern as the relationship between precipitation and malaria becomes significant at lower levels of precipitation. Our results provide evidence that both temperature and precipitation have non-linear effect on malaria mortality across countries. We also find that optimal thresholds for both these climatic exposure variables are lower than previously estimated. These estimates can be used to understand the impact of future changes of temperature and precipitation on malaria mortality.

2.7 Conclusion

We examine the effect of temperature and precipitation on malaria mortality in a cross-country paradigm using panel data. Quantile regression framework has been used to examine if climatic exposures have differential effects on the entire distribution of malaria mortality rates. This is one of the first papers to provide empirical evidence of the impact of temperature and precipitation on malaria mortality on a global scale using Quantile regression. Furthermore, we estimate the updated optimal temperature and precipitation levels for malaria mortality. Our results confirm the non-linear nature of the relationship between the climatic exposure variables and malaria mortality and can be used to predict the impact of future changes of temperature and precipitation on malaria mortality.

Our results suggest that the optimal temperature for countries with relatively low levels of mortality is 32.6℃; slightly higher than the range of 20℃ - 30℃ estimated by the previous literature. While, the optimal temperature estimated for countries with relatively high malaria mortality rate is 24.07℃; lower than that suggested recently by Mordecai et al. (2013) and between 5℃ - 6℃ lower than that suggested by the papers using mechanical models (Martens et al., 1998 and Parham and Michael 2010). This is a cause for concern as it would require less of an increase in mean temperature in these countries to reach the peak malaria mortality. Currently, 37% of the high malaria mortality countries in our dataset are below this threshold. This might be a major cause of concern in regions such as the sub-Saharan Africa and some parts of South Asia, which are already exposed to high levels of malaria mortality. As for precipitation, in countries with relative high malaria mortality - the optimal level is estimated to be 934.4 mm per year; lower than the 80 mm per month suggested in the existing literature.

It is difficult to discern the impact of temperature and precipitation from the existing literature as they have been rarely considered together, this paper includes both these variables and is one of first to utilize the updated global malaria mortality dataset and provide empirical evidence on the relationship between temperature, precipitation, and malaria mortality (most of the existing literature has focused on malaria transmission). This paper uses quantile regression analysis to provide updated turning points for the climatic exposure variables on their impact on malaria mortality and concludes that temperature and precipitation have differentiated impacts across countries. We provide new estimations for the optimal temperature and precipitation levels for malaria mortality, this has important policy implications in that regions that are already at the optimum levels of temperature and precipitation or are close to the optimum can be especially targeted.

It is difficult to discern the impact of temperature and precipitation from the existing literature as they have been rarely considered together, this paper includes both these variables and is one of first to utilize the updated global malaria mortality dataset and provide empirical evidence on the relationship between temperature, precipitation, and malaria mortality (most of the existing literature has focused on malaria transmission). This paper makes three major contributions to the existing literature; (i) it is one of the very papers analyzing the effects of temperature and precipitation on malaria mortality simultaneously - most of the existing literature deals with them separately, (ii) it utilizes a quantile regression framework to investigate the relationship - this allows us to investigate the differentiated impact of climatic exposure on countries with different levels of malaria mortality, (iii) provides updated optimal conditions for malaria mortality with respect to climatic exposure and (iv) controls for health expenditure across countries as a proxy for malaria eradication efforts.

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Chapter 3

Impact of Climate Variability on Crop Yields

Abstract

The impact of climate change is increasingly evident through movements of climatic variable such as temperature and precipitation. Quantification of these impacts are necessary in order to understand the economic implications of these changes. Agriculture is sensitive to changes in the climatic variables they are direct components of the production process and variability of these variables from the long-term mean is likely to affect crop growth. This paper combines historical crop yield data for rice and maize with corresponding temperature and precipitation data during 1971-2012 to study the impact of changes in variability on crop yields. Using Quantile Regression, we find that increases in variability of both temperature and precipitation from the long-term mean may benefit crop yields up to a certain degree, however, as the variability exceeds this threshold, there will likely be negative impacts. The results also demonstrate that temperature variability beyond 0.57℃ (0.72℃ for maize) will negatively impact rice yield in low yield countries while precipitation variability beyond 178 mm (192 mm for maize) would be detrimental. While crops yields usually acclimatizes to long-term means and are able to adjust to moderate variability, high degrees of climatic variability will most likely have a negative effect.

Keywords: Climate change, Crop yields, Rice, Maize, Temperature, Precipitation, Quantile Regression.

Preliminary draft: Please do not quote.

3.1 Introduction

The impact of climate change is increasingly evident through movements of climatic variable such as temperature and precipitation. Agriculture is one of the most highly exposed sectors to the climate and climatic variability. Quantification of this impact is necessary in order to understand their economic and social implications. Agriculture is very sensitive to changes in the climatic variables such as temperature and precipitation as these climatic variables are a direct component of the production process. Agriculture only contributes about 6.6% of the world's GDP, while 37% of the world's labor force is involved in this sector (IMF, 2015), with developing countries accounting for a disproportionate share of the total. Furthermore, it is worth noting that 40% of women around the world are employed in the agricultural sector, 67% belonging to developing countries. Many of the studies examining the effects changes in climatic variables on agriculture have focused on the effects of either mean temperature or precipitation on crop yields. Thus there is a need for cross country analysis of the impact of changes in the climate variables on crop yields.

If the argument that changes in climate variables has adverse effects on crop yields holds, then countries with high agricultural contribution to GDP are at high risk from the perspectives of both growth and food security. There is evidence that crop growth and production is affected by changes in the long-term trend of the climate variables (Schlenker and Roberts, 2006; Battisti and Naylor, 2009; Lobell et al., 2011; Butler et al., 2013; and Wheeler et al., 2013). However, in order to test this relationship across countries, it is important to examine the impact of variability in temperature and precipitation. This paper will provide an analysis of the effects of changes in the variability of temperature and precipitation on crop yields using Quantile regression on a cross-country framework.

There is conflicting evidence on the possible effects of these variables on crop yields. Higher temperatures may lead to more flooding and eventually reduce crop yields; however, it can also have a favourable impact in regions with relatively cooler growing seasons or have an adverse impact in regions with already high temperature levels (Mendelsohn et al., 2007). Precipitation affects the moisture content of soil, thus changes in precipitation can directly influence crop yields. Initial increases in precipitation allow fertilizer to mix better and increase yields; however, above a certain threshold, the absorption capacity of the soil decreases leading to an anticipated reduction in yields. Different crops also have different optimal growing conditions with regards to temperature and precipitation. Movement away from these conditions may be damaging for crops, especially in countries where the current temperature and precipitation levels are already close to the tolerance limit (FAO, 2000).

This paper combines historical crop yield data on two of the major crops grown around the world, rice and maize, with the corresponding temperature and precipitation data from 1971-2012 to investigate the impact of variability from the long-term mean. Based on the standard finding that agricultural products usually have inelastic demand, a negative shock in output will trigger a disproportionate rise in price, a phenomenon well documented for the US and developing countries (Schlenker et al., 2006). It is likely that adverse impacts of climate change are likely to be heavily linked with food security, poverty and inflationary prospects. While growth of crops usually acclimatise to long-term means and adjust with moderate variations, climatic variability can be detrimental. While the theoretically optimal level of variability should be as close to zero as possible, in reality changing climatic conditions means that crops also adapt to new optimal conditions and as a result different levels of climatic variability will likely have differentiated effects on crop yields. This paper finds that increases in temperature and precipitation variability from the long-term mean exceeding a certain threshold has an adverse affect on both rice and maize yields, especially in countries with relatively low yields.

The rest of the paper is structured as follows: Section 3.2 provides a summary of the relevant literature; Section 3.3 provides a summary of the data and the sources. Section 3.4 of the paper explains the methodology and econometric framework used, while Section 3.5 discusses the results and Section 3.6 concludes this study.

3.2 Literature Review

The scientific community has long argued that changes in climatic variables such as temperature and precipitation significantly impact crop yields. Reilly et al. (1994) find as temperatures move away from the favorable growing temperature of a crop then the growth of the crop is adversely affected. Similarly, if variability in temperatures is high, crop yields are lower. The authors conclude that places that are too hot or are too close to the optimum temperature are likely to suffer the most. Although increases in precipitation may offset the effects of increases in temperature, this will likely vary from region to region and over a certain threshold precipitation will also have an adverse impact (Van de Guijin et al., 1996).

Agriculture is believed to be one of the most vulnerable sectors to adverse climate change. The same climatic forces that are critical to agricultural productivity can be damaging to crop yields due to increased variability and increased frequency of extreme events. The literature linking climate change and crop yields is vast and spans several disciplines. Agricultural economists have used simulation models and simple regression techniques to study the physiological process of crop growth. Most agricultural economists view the relationship between temperature and crop yields as non-linear (Schlenker and Roberts, 2008).

The next generation of studies uses hedonic pricing models to examine the effects changes in the climate change on crop yields. The main idea behind this particular group of papers is to control for land characteristics and in effect control for changes in the climatic variables. These authors use reduced-form linear regression models to study the impact. Mendelsohn et al. (1996a), using quadratic measures for temperature and precipitation for certain months, estimates that a 5° F increase in mean temperature is likely to result in changes in land rent ranging from a loss of 4.9% to a gain of 1.2%. However, estimated changes in farmland values are often found to be negative in this paper which is in violation of economic principles asset valuation (Darwin, 1999).

Lobell and Field (2007) estimate that mean temperature increases since 1980s has caused losses of approximately of USD 5 billion because of negative effects of changes in optimum temperature on the major crops grown in the US such as wheat, maize and barley. Olesen and Bindi (2002) argue that since the major portion of irrigation to agricultural production in the world comes from rain, changes in precipitation will patterns likely have an impact on crop production. Christensen et al. (2007) suggest that change in seasonal variation in precipitation rather than change in mean precipitation is more likely to affect crop production. Using cross-county farming data, Mendelsohn et al. (1994, 1996b) concluded that, depending on the location the impact of high temperatures range from slightly adverse to largely beneficial.

Nordhaus (2006) used a sample of 72 country effects and found that temperature has a negative effect on output when measured on per capita basis but oddly positive when measured on a per area basis. While Dell et al. (2008), using panel data on 136 countries from 1950-2003 suggest that a 1°C rise in temperature tends to reduce economic growth in that year by 1.1 percentage points. This paper also suggests that higher temperature has negative effects on crop yields within poor countries but not in rich countries. However, a cross-sectional study of crop production during the period 1960-2000 by Mendelsohn et al. (2007), shows that change in temperature and precipitation changes have caused estimated global impacts ranging from a loss of 0.05% to a gain of 0.9% of agricultural GDP. A number of recent papers (Rowhani et al., 2011; Butler et al., 2013; Ortiz-Bobea and Just, 2013; and Ray et al., 2015) provide insight on the relationship between climatic exposure and crop yields using high resolution spatial data. Deschenes and Greenstone (2011) and Ortiz-Bobea (2012) use statistically estimated response functions to estimate the impact of climate change on daily temperature and soil moisture. However, It is important that we examine this relationship on a national scale in order to compare the effects of climatic exposure on high and low yield countries.

Many papers in the existing literature have also focused on the impact of changes in the mean of climatic variables on crop yields, however, one of the major concerns relates to changes in variability and extremes. This paper will investigate the possible effects of changes in climatic variability on quantiles of the crop yield distribution. Thus, in this framework crop yields will be a function of the climatic variables and country-year fixed effects (Koenker, 2004), to control for unobserved country-specific, time-invariant effects. Quantile regression, in particular, allows the study of the effects of climate variables on agricultural production efficiency. We argue that the impact of changes in climatic variables such as temperature and precipitation on crop yields across countries is not homogeneous.

3.3 Data and Summary Statistics

The data for temperature and precipitation comes from the Global Historical Climatology Network (GHCN-M) version 2 for precipitation (Peterson and Vose, 1997) and version 3 for temperature (Lawrimore et al., 2011). GHCN-M is an integrated dataset of temperature, precipitation, and pressure records managed by the National Climatic Data Center, Arizona State University, and the Carbon Dioxide Information Analysis Center (Menne et al., 2012). This dataset contains monthly mean temperature and precipitation data from across the world. The station level data has been aggregated to estimate the annual averages for each country. Data on crop yields has been collected from the Food and Agriculture Organization (FAO) .

The summary statistics suggest that rice is the higher yield crop and the mean temperature in the panel is 18.1°C which is 0.65°C higher than the centennial mean (IPCC, 2007). The average rice yield is 29,500 (hg/ha) during 1971-2012 is slightly higher than the average for maize yield of 27,375 (hg/ha) during the period.

3.4 Methodology

Since we are interested in the long-term variability of climatic variables, variability for precipitation and temperature is estimated by taking the squared difference for each annual observation for each country i from the mean ($\bar{P}_i$ and $\bar{T}_i$) of the entire panel for each country;

$$Temperature\,variability = (T_{it} - \bar{T}_i)$$
$$Precipitation\,variability = (P_{it} - \bar{P}_i)$$

3.4.1 General Framework

In order to investigate the impact of climate change on the agricultural crop yields, we estimate the following function;

$$lny_{it} = \alpha_i + \gamma_t + \beta_1 T_{it} + \beta_2 T_{it}^2 + \beta_3 P_{it} + \beta_4 P_{it}^2 + \epsilon_{it} \tag{3.1}$$

Where *lny* represents the natural logarithm of crop yields in a given year in country i in year t, α_i represents country fixed effects and γ_t represents time fixed effects. Crop yield is expressed in log units, thus a given change in either T (Temperature variability) or P (Precipitation variability) will produce percentage increases in crop yield, independent of the absolute levels of production. Based on evidence suggesting that most crops have optimal conditions (temperature and precipitation) for growth and that deviations from these conditions are damaging for crops, a squared term for both temperature and precipitation is included. While papers using high resolution temporal geo-spatial data are able to provide better insights into the impacts of climatic variables on sub-national and local sites, they are unable to provide cross-country comparisons as conducted in this paper.

3.4.2 Quantile Regression

Quantile regression offers a method for inferring the conditional distribution of an outcome of interest over the entire support of its distribution. This allows us to examine the effect of covariates at different points on the distribution. The quantile regression parameter represents the effect of a one unit change of the explanatory variables on the specified percentile of the outcome variable. This allows us to compare if some quantiles of crop yields may be more affected by the explanatory variables. If countries with lower yields are affected more by changes in climatic variability, then there is a cause for concern. The quantile regression model can be expressed as;

$$lny_i = \alpha_t + \gamma_{it} + \beta_1 T_{it}^{(p)} + \beta_2 T_i^{2(p)} t + \beta_3 P_{it}^{(p)} + \beta_4 P_{it}^{2(p)} + \epsilon_{it}^{(p)} \tag{3.2}$$

The quantile function completely characterizes the distribution function of a random variable and as a result it possible to estimate the country level features of the complete condition yield. Quantile regression also allows for the country-specific heterogeneity (by including the fixed effects) and the heterogeneity of covariate effects (Koenker, 2004). The estimated coefficients of the explanatory variables from quantile regression also vary based on heterogeneity. However, inclusion of individual fixed effects often changes the interpretation of the coefficients of these variables. Koenker (2004) and Harding and Lamarche (2009) focused on treating the fixed effects in the context of a penalized estimator by separating the estimation of the fixed effects and the other covariates though an L2-penalty [1]. However, since the L1 penalty allows the shrinkage of the fixed effects and as a result decreases the variability in the estimation of β, this method, along with setting the penalty term equal to zero, is used in this analysis. We used the *Quantreg* package in R (Koenker, 2015) for all our estimations.

3.5 Results

Quantile regression allows us to examine if there are differentiated impacts of climate variability on the different efficiency levels of crop production. The value of the shrinkage parameter is an ongoing research question, thus for the purposes of this study it has been set to the simplest homogeneous settings of the ratio of the scale parameters of the fixed effects and the idiosyncratic errors.

3.5.1 Rice

The results from the quantile regression for rice yields are presented in Table 3.1. Column 1 provides the results for high yield countries and the estimation suggests that the turning point for temperature variability is 0.68℃ (*maxima*). Deviation from the long-term mean beyond this level is likely bring about a negative impact on rice yields. While for the low yield countries (Column 2), the turning point for temperature variability is 0.57℃. Thus, a lower degree of variability in temperature is expected to be more detrimental to rice yields in low yield countries compared to high yield countries.

Table 3.1: Quantile Regression Results for Rice Yields

Quantiles	75^{th} Quantile	25^{th} Quantile
Variables	Rice Yield	
Temperature Variability	1.06***	0.88***
	(-0.006)	(-0.006)
Squared Temperature Variability	0.78***	0.77***
	(-0.002)	(-0.002)
Precipitation Variability	33.66***	31.71***
	(-0.062)	(-0.059)
Squared Precipitation Variability	-0.081***	-0.089***
	(-0.003)	(-0.004)
Constant	9.82***	8.03***
	(-0.018)	(-0.018)
Observations	1198	1,290
Number of Countries	30	34

Standard errors in parentheses
*** p>0.01, ** p>0.05, * p>0.1.

[1] L1 and L2 penalized estimation methods shrink the estimates of the regression coefficients towards zero relative to the maximum likelihood estimates. The purpose of this shrinkage is to prevent over-fit arising due to either collinearity of the covariates or high-dimensionality. Although both methods are shrinkage methods, the effects of L1 and L2 penalization are quite different in practice. Applying an L2 penalty tends to result in all small but non-zero regression coefficients, whereas applying an L1 penalty tends to result in many regression coefficients shrunk exactly to zero and a few other regression coefficients with comparatively little shrinkage (Koenker and Bassett, 1978).

As for precipitation, variability beyond 207.8 mm per year will have an adverse impact for high yield countries while the turning point for low yield countries is 178.1 mm of rainfall per year. These estimates suggest that a lower degree of climate variability is likely to have a negative impact on countries with low rice yield. All the coefficients in 3.1 are statistically significant.

3.5.2 Maize

The results from the quantile regression on maize yields are presented in Table 3.2. The estimates in Column 1 shows that the *maxima* is at 0.79°C for high yield countries, while for the low yield countries, it is 0.72°C - these figures are slightly higher than those estimated for rice yields. These results suggest that, it would require less temperature variability from the long-term mean to have an adverse impact on maize yields in low yield countries. As for precipitation (Column 2), rainfall variability beyond 212.84 mm per year is likely to negatively impact maize yields in high income countries while a far lower variability of 191.7 mm per year in low yield countries would have a negative impact in low yield countries.

Table 3.2: Quantile Regression Results for Maize Yields

Quantiles	75^{th} Quantile	25^{th} Quantile
Variables	Maize Yield	
Temperature Variability	1.50***	1.05***
	(-0.008)	(-0.007)
Squared Temperature Variability	0.95***	0.73***
	(-0.003)	(-0.004)
Precipitation Variability	41.29***	33.74***
	(-0.062)	(-0.059)
Squared Precipitation Variability	0.097***	0.088***
	(-0.003)	(-0.004)
Constant	11.66***	10.15***
	(-0.029)	(-0.021)
Observations	2207	972
Number of Countries	57	24

Standard errors in parentheses
*** p>0.01, ** p>0.05, * p>0.1.

In summary, high degrees of variability from the long-term mean of both temperature and precipitation is likely to have an adverse impact on both rice and maize yields. Furthermore, these results demonstrate that in case of low yield countries, a lower degree of variability of the climatic exposure will start to have a negative impact on crop yields. This is a cause for concern, as growth of crops acclimatise to the long-term mean and can often adjust with moderate variations, however, dramatic climatic variability can harm the adjustment process.

3.6 Conclusion

We find that increases in variability of both temperature and precipitation may benefit crop yields up to a certain degree. However, as the variability exceeds that threshold, it will have a negative impact. Our results demonstrate that annual temperature variability beyond 0.57℃ (0.72℃ for maize) would negatively impact rice yield in low income countries while rainfall variability beyond 178 mm (192 mm for maize) would be detrimental. While growth of crops usually acclimatise to long-term means and adjust with moderate variations, high climatic variability results in the conditions moving away from the optimum and has negative impacts.

The empirical estimations in this paper are consistent with both the existing literature and theory of climate change and agriculture. After controlling for changes in the climatic variables to analyze their impacts on crop yields, we find that increases in variability of both temperature and precipitation from the long-term mean are expected to benefit crop yields up to a certain extent. However, as the variability exceeds a certain threshold which is the major cause for concern among climatologists, it is expected to have a negative impact on crop yields. As variability of temperature causes the conditions to move away from the optimum growing conditions for crops, yields are expected to fall. At the same time, as variability of precipitation increases, the optimum absorption capacity of soil is affected and has an adverse affect crop yields. These results are consistent with the findings from agronomic literature (Battisti and Naylor, 2009). This is likely because crops can adjust to variability below a certain threshold, beyond which there seems to be a negative impact on yields. We find that it would require a lower degree of increase in temperature and precipitation variability to have an adverse impact on lower yield countries and this is a major cause of cause concern low yield countries are also most likely to be less advanced and poor.

The most important finding of this paper is that the degree of variability from the long-term mean required to have a negative effect is lower for low yield countries. As climate change adversely affects crop yields, the consequent implications will be multi-fold. Since the countries in the panel produce around 87% of the total crop production, this will have a negative impact on food supply and prices in the world market. As a result agricultural income will be affected and will be felt by a major portion of the labor force in these countries. The World Bank estimates that a 10% increase in domestic food prices could push and additional 64 million people around the world into poverty. Thus issues regarding food security and poverty alleviation will also be adversely affected.

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Chapter 4

Development, Climate Change Adaptation, and Maladaptation: Some Econometric Evidence

Abstract

This paper examines the determinants of climate related disasters and attempts to estimate the presence of adaptive capacity in terms of per capita income and population density elasticities. We find evidence of adaptive capacity in a *weak* form both in terms of income and population density elasticities over our entire sample. That is, damages are in fact increasing with income and population, but less than proportionally. There is also evidence of countries improving their adaptive capacity over the long run but of maladaptation occurring in the short run. Repeating the analysis by splitting the countries by per-capita income levels, we find that higher income countries show adaptive capacity in a *strong form*, i.e. damages decrease with GDP, while lower income countries highlight exactly the opposite behaviour. Finally, using Granger causality tests for panel data, we find evidence of increase in GDP per capita Granger causing climate related damages for lower income countries but not in higher income countries.

Keywords: Climate Change, Climatological Damages, Adaptation, Panel Granger Causality.

Preliminary draft: Please do not quote.

4.1 Introduction

The total estimated damage from climate related disasters between 2011 and 2013 was US$ 641 billion while the average number of deaths and people affected between 2003 and 2012 were 106,000 and 216 million, respectively. How will these damages and fatalities change in the coming years? Under the theoretical view point, expectations of both increasing and decreasing trends can be supported. Indeed, on the one hand development associated to higher population density, physical capital, and ultimately GDP would itself determine a higher exposure to climate stressors and thus expected damages. This trend can be exacerbated by climate change that can increase the frequency and intensity of some form of climatological events (IPCC, 2012). On the other hand, development associated to more advanced technologies, knowledge and resource availability would determine a higher adaptive capacity and thus lower expected damages.

A number of papers have studied the determinants of natural disasters originating a rapidly growing body of research. The related, mostly econometric literature has focused on the linkages between damages and different indicators of economic development. The general finding is that developed societies tend to be less vulnerable; however, the relation between vulnerability and development is not always straightforward with studies pointing to non-linear or even negative patterns. In a seminal paper Albala-Bertrand (1993) argues that countries with weaker economies are more affected by climate related disasters. Horwich (2000) also suggests that the level of wealth is critical for a country's response to a natural disaster. Using quantile regression, Keefer et al. (2011) test differential impacts of earthquakes, floods, and tropical cyclones across various damage bins on disaster propensity. They find that mortality due earthquakes are lower in countries with high payoffs to mortality prevention and mortality is higher in autocracies and in more corrupted countries but without controlling for many other relevant socioeconomic variables. Mendelsohn et al. (2012) found damage elasticity to income to be 0.42 and population density to be -0.20 concluding that both provide an evidence of adaptation linked to development.

Kellenberg and Mobarak (2008) identify of a nonlinear relationship between economic development and vulnerability to damages from natural disasters, with risk initially increasing with higher incomes as a result of changing behaviors. Cavallo et al. (2010) using simple regression techniques conclude that countries with higher population, land area, and GDP are more exposed and hence suffer higher damages from earthquakes. Their findings are thus conflicting to the argument that richer countries have more adaptive capacity.

A stream of literature (Kahn, 2005; Skidmore and Toya, 2007; Stromberg, 2007; Raschky, 2008; and Plumper and Neumayer, 2009) focuses on the role of political and institutional variables. The general finding is that increases in education, trade openness, financial sector strength, coupled with better institutions and stable democratic regimes help reduce the impact of disasters. A few papers have also explored the link between political accountability and damages from natural disasters (Besley and Burgess, 2002; Eisensee and Stromberg, 2007 and Healy and Malhotra, 2009) finding that greater accountability tends to lower damages.

One criticism of the current literature is the fact that often social, macroeconomic, institutional and political regimes characteristics have not been explored together - thus raising the possibility of missing variables bias. Furthermore, the studies mostly use annual means of socioeconomic data and do not consider the possibility of heterogeneous adaptation or maladaptation across countries. With this paper we try to answer two questions. First, which effect prevails in determining climate vulnerability across societies? Is it the increasing exposure due to more assets at risk or the increasing adaptive capacity effect? Second, which is the direction linking damages and development? Are the former driving the latter or vice versa? For this purpose we analyze the determinants of a set of weather/climate damages associated to: drought, extreme temperatures, wildfire, floods, landslides, and storms [1] between 1980 and 2012. We address some of the limitations of the existing literature by;

- Including several social, macroeconomic and institutional variables to empirically test the evidence of adaptation/adaptive capacity estimating damage elasticity to income and population density.
- Not assuming aprioristically linearity among the variables nor homogeneity across countries with different wealth and development levels.
- Furthermore, providing a panel Granger causality analysis to determine if the relationship between income and climatological damages is bidirectional.

We find evidence of adaptive capacity in a *weak* form both in terms of income and population density elasticities over our entire sample. That is, damages are in fact increasing with income and population, but less than proportionally. There is also evidence of countries improving their adaptive capacity over the long run, but of maladaptation occurring in the short run. Repeating the analysis splitting the sample by per-capita income levels, we find that higher income countries show adaptive capacity in a *strong form*, i.e. damages decrease with GDP, while lower income countries highlight exactly the opposite behaviour. Finally, using Granger causality tests for panel data, we find evidence of increase in GDP per capita Granger causing climate related damages for lower income countries, but not in higher income countries.

4.2 Methodology and Data

The aim of the paper is to explain climate related economic damages by controlling for socio-economic indicators along with measures of risk, institutional capacity, and stability of democratic regimes. As a conceptual starting point, we assume that countries solve an optimization problem with the goal to minimize total costs from climate disasters. Without adaptation, for a particular climatological disaster, c, countries' damages, D_c, can be written as;

$$D_c = \alpha_1 \, . \, Y \, . \, \alpha_2 \, . \, Pop \, . \, CD_c^{(\alpha_3)} \tag{4.1}$$

According to Equation 4.1 damages will be higher as income, Y, and population density, Pop, increase. In the Equation 4.1, CD_c represents characteristics of the climatological disaster c. However, adaptation can protect against damages from disasters. Assuming that adaptation (expressed as the capacity to reduce the damage) also depends positively on income, population density, an adaptation function can be expressed as;

$$A = \gamma_1 \, . \, Y^{(\gamma_1)} \, . \, Pop^{(\gamma_2)} \tag{4.2}$$

[1]As coded in the EM-DAT database

Finally, total damages from climatological disasters can be written as a multiplicative function of the two functions expressed above;

$$TD_c = AD_c = \alpha_1 \, . \, \gamma_1 \, . \, Y^{(1-\gamma_1)} \, . \, \alpha_2 \, . \, Pop^{(1-\gamma_2)} \, . \, CD_c^{(\alpha_3)} \tag{4.3}$$

In Equation 4.3 the exponents of Equation 4.2 appear with the inverted sign as adaptation lowers damages. For the purposes of this paper, we focus on income/wealth and population density as primary determinants of adaptive capacity. We assume that if $\gamma_1 = \gamma_2 = 0$ in Equation 4.3 suggests no evidence of adaptation. In other words, if the damage elasticities of income and population density are equal to 1 then it can be concluded that no adaptation has taken place. However, if the coefficients of income and population density elasticity are lower than 1 or negative then there is evidence of adaptation. We call the former case with damages increasing but less than proportionally with income and population density *weak* adaptation and the latter with damages decreasing with income and population density *strong* adaptation. On the other hand, if the elasticities are greater than 1, meaning that increases in income and population density will lead to more than proportional increases in damages from climate related disasters then we have evidence of maladaptation.

Equation 4.3 can be conveniently transformed in log-log form and estimated with fixed effects controls to control for time-invariant effects and reduce the threat of omitted variable bias. In our case, including fixed effects, controls for the average differences across countries in any observable or unobservable predictors. Fixed effects models are also based on less restrictive assumptions than random effects as they allow unobservable variables to have whatever associations with the observed variables regardless of whether they have been explicitly modelled or not (Angrist and Pischke, 2009). The general specification with country α and time γ effects can be written as;

$$d_{it} = X\beta_{it} + R_{ij}\delta + \alpha_i + \gamma_t + \epsilon_{it} \tag{4.4}$$

Where d_{it} is the log of total damages in country i from climate related disasters in the year t, R is a measure of risk to a climate hazard in country i in year t, finally X_{it} is a the logged vector of socio-economic characteristics of country i in a given year t. More specifically, the explanatory variables are as follows;

Log of GDP per capita: It is used as an indicator for wealth and income of a country and thus indirectly of its potential adaptive capacity. As mentioned above, damage elasticity to GDP provides us with an indication of the existence of adaptation.
Log of population density: It is also meant to signal evidence of adaptive capacity should a country's damages increase less than proportionally with it.
The Polity index: It examines concomitant qualities of democratic and autocratic authority in governing institutions and incorporates component measures such as key qualities of executive recruitment, constraints on executive authority, political competition and changes in the institutionalized qualities of governing authority. It essentially captures those mixed traits by subtracting a country's rank order score on autocracy from its rank order score on democracy. This indicator is highly sensitive (it employs a 21 point scale). Moreover, it allows considering both the degree and the duration of democracy in any given country-year. It is meant to capture if and how the quality of institutions influences the damage and therefore its role in determining a country adaptive capacity.
Government expenditure as a share of GDP: It should capture the weight and interventionism of the

public sector in the economy. It is included to investigate the effectiveness of government assistance and to some extent the impact of government size on damages.
The share of agricultural sector of GDP: It is used as an indication of a country's sensitivity to climatological disasters. The idea is that agriculture is a typical climate-dependent activity, therefore, the higher the share of agriculture's contribution to GDP of a country, the higher the risk of damages due to climatological disasters for that country.
Risk: Following Adger et al. (2004) we define this variable as the ratio of the number of people killed to the number of people affected by climatological disasters. This is included as an indicator of a country's vulnerability/sensitivity to climatic damages and is used as a proxy indicator for climatic risk for the population.
Openness is defined as the share of a country trade as percentage GDP . It is an index of a country's integration with the global economy and is included to test if access to international markets, allowing easier inflow of foreign goods and investments, can act as a smoothing factor on its damages.
Temperature and precipitation are indicators of a country's exposure to the climate as climatological events are affected by both rising means and rising variability of these variables (Schar et al., 2004).

Our response variable is the natural log of US dollar denominated damages from natural and climatological disasters - drought, extreme temperatures, wildfire, floods, landslides, and storms. Our dataset is an unbalanced panel combining data from three datasets (climate disaster, socio-economic, and climatic) between 1980 and 2012 for 104 countries. Damages from climatological disasters at the country level are taken from the EM-DAT (Guha-Sapir et al., 2012) database, and matched with World Development Indicators (World Bank, 2013) that provide all the macroeconomic and socio-economic indicators. Data for democratic regime qualities have been taken from the Polity IV database (Marshall and Jaggers, 2002 and Polity IV, 2013). Data on temperature and precipitation derive from Global Historical Climatology Network (GHCN-M) version 2 (Peterson and Vose, 1997) for precipitation and version 3 for temperature (Lawrimore et al., 2011).

As with most econometric analysis, measurement errors are of concern. Since damages suffered from disasters are difficult to quantify, it is possible that some measurement errors are present in the EM-DAT database. However, a number influential papers state the reporting standards of this particular database are acceptable and in order for a disaster to be included it must be meet a number of criteria. Furthermore, we use the damages data only as the dependent variable and as such the covariates are free from bias. While it could be argued that endogeneity remains an issue, we assume, in the first round of estimates, that GDP per capita and population density are exogenous. Then, we examine the determinants of climate disasters and test if adaptive capacity differs between the short and long run by exploring different lag structures of the covariates. Finally, we test explicitly the direction of the link between the dependent and the explanatory. All the specifications used, consider heteroskedasticity corrected standard errors.

4.3 Results and Discussion

4.3.1 Mean Regression Framework

Table 4.1 reports the result of the simpler fixed effect models without lagged variables of the explanatory variables. Statistically significant income elasticities turn out to be robust across the models, with values ranging from 0.581 to 0.739. This suggests that as income of countries increase, damages from climatological disasters do not increase proportionally. Thus in the overall dataset, there is evidence of what we call *weak* adaptive capacity among countries with respect to income. It is likely that as a country's income increases, it is able to allocate greater funding towards adapting ex ante and ex post to climatological damages, e.g. constructing dams to protect against flood damages and rehabilitation of population living in coastal areas. Nonetheless, it is not possible to offset completely the higher exposure given by the more assets at risk.

In Table 4.1, in columns 2 and 3, coefficients for log of population density are also statistically significantly positive, and lower than one. This further provides evidence of adaptation and suggests that an increase in population density does not bring about a proportionate increase in climatological damages. This could be due to greater precautions being taken in densely populated and highly urbanized areas and governments undertaking more programs and projects to protect against climatological disasters.

Column 3 also shows, in accordance with intuition, that the larger the agricultural share in GDP, the higher the damages from climatological disasters. This is a consequence of a higher share of the economy particularly sensitive to natural disasters such as floods and droughts. The polity variable is negative and statistically significant, suggesting that stability and democratic qualities of regimes plays an important role in helping to reduce damages from climatological disasters. The same holds for the openness index which suggests that well developed trade relationships can help a country to smooth negative consequences of climate disasters. This can happen through an easier substitution of foreign demand and supply for the domestic ones should the latter be negatively affected by climate impacts and also, more directly, through an easier access to foreign aids. However, the coefficients for the share of government expenditure of GDP and risk are not statistically significant.

Table 4.1: Panel Regression Results

Variables	Dependent Variable: Log of Damages		
Log of GDP per capita	0.739***	0.631***	0.581***
	(-0.075)	(-0.073)	(-0.089)
Log of Population Density	0.125	0.153*	0.192**
	(-0.091)	(-0.083)	(-0.091)
Govt. Exp./GDP		0.003	0.006
		(-0.02)	(-0.022)
Risk		0.0123	0.019
		(-0.023)	(-0.023)
Agriculture Sector/GDP			0.013**
			(-0.001)
Openness			-0.501**
			(-0.141)
Polity			-0.019**
			(-0.007)
Constant	11.14***	1.20***	10.56***
	(-0.812)	(-0.755)	(-0.81)
Country FE	Yes	No	Yes
Year FE	No	Yes	Yes
Observations	1,022	985	972
Number of Countries	104	95	91

Standard errors in parentheses
*** p>0.01, ** p>0.05, * p>0.1.

4.3.2 Long-Run Variation

In this section we explore the impact of lagged covariates on climatological damages and attempt to highlight any differential impact between the short and the long run. We also include temperature and precipitation as indicators of climatic exposure variables. The first striking difference with the static analysis reported in Table 4.1 is that the coefficient for contemporaneous income elasticity in Table 4.2 is greater than one and statistically significant, suggesting evidence of maladaptation in the short-run. However, the elasticity is lower than one in the long-run. This seems to point out that adaptive capacity of countries does improve with respect to income, but that this is a process requiring time. This finding is strengthened by the coefficient for population density elasticity; it is just slightly lower than one in the short-run, but much lower than one in the long-run, providing further evidence that adaptive capacity is a dynamic process. In the specific case of population this could indicate more protective adaptation and development programs being undertaken over time in areas with high population density.

Table 4.2: Regressions with Lagged Covariates

Variables	Dependent Variable: Log of Damages
Log of GDP per capita	1.491***
	(-0.410)
Log of Population Density	0.792**
	(-0.044)
Govt. Exp./GDP	0.061
	(-0.520)
Risk	0.026
	(-0.023)
Agriculture Sector/GDP	0.018
	(-0.013)
Openness	-0.322*
	(-0.145)
Polity	-0.011
	-0.059
Lagged Log of GDP per capita	0.660***
	(-0.077)
Lagged Log of Population Density	0.330**
	(-0.083)
Lagged Govt. Exp./GDP	0.019***
	(-0.003)
Lagged Risk	0.03
	(-0.023)
Lagged Agriculture Sector/GDP	0.013**
	(-0.001)
Lagged Openness	-0.511
	(-0.143)
Lagged Polity	-0.013**
	(-0.009)
Log of Temperature	0.007**
	(-0.001)
Log of Precipitation	0.003**
	(-0.019)
Constant	5.642
	(-6.335)
Observations	776
Country FE	Yes
Year FE	Yes
Number of Countries	91

Standard errors in parentheses
*** p>0.01, ** p>0.05, * p>0.1.

Results in Table 4.2 also show that government expenditure is positive and significant only in the long run. This outcome, similar to that of Toya and Skidmore (2007) seems to point out that countries with higher share of public expenditure over GDP tend to dynamically experience higher climate related losses. This can be explained as a signal of lower efficiency of the public vs the private sector. In our sample this behaviour can be driven by the presence of developing countries more easily characterized by ineffective relief efforts and corruption in government programs. Similarly, but with opposite effect, regime characteristics: democratic regimes seem to be less vulnerable to climate damages, but this relation is significant in the long-run, and with no effect in the short- run. Temperature does have a positive and significant impact on climatological damages in the long-run, but not in the short-run, while precipitation seems to have no significant impact, although the coefficients are positive in both the short and long-run. Ultimately, the inclusion of these two variables does not to change the significance level of the other variables. Nonetheless, it should be noted that the dependent variable is an aggregated measure of damages and the results could well be different if individual disaster categories were considered. In summary, the main finding from the dynamic analysis is that building up adaptive capacity or effective adaptation is a process taking place over time.

4.3.3 Examining Determinants across Income Levels

It is critical to examine whether the results from the above specifications are robust across different income levels. In this regard, we use country and year fixed effects along with standard errors clustered by country in a further set of regressions. Results are reported in Table 4.3. The major message conveyed by the analysis suggests, somewhat similarly to Kellenberg and Mobarak (2008), a bell-shaped relation between damage and per capita income, or, differently said, evidence of insufficient adaptive capacity, if not maladaptation, (at) in low income (levels) countries and efficient *strong* adaptive capacity (at) in high income (levels) countries. The GDP per capita elasticities for the low income countries are indeed positive and larger than one (ranging from 1.701 to 1.960). This could be interpreted as the dominance, at low per-capita income levels, of the *assets-at-risk* or *exposure* effects over adaptive capacity. Accordingly, increasing GDP raises vulnerability. At the higher income levels, the relation reverses: per capita GDP coefficient is larger than one, but negative. Thus more GDP reduces damages highlighting that with development more resources are available for investment in resilient infrastructure and disaster preparedness, the factors most likely influencing adaptive capacity, eventually overcoming the *assets-at-risk* effect.

Table 4.3: Regressions across Income Levels

Income Range	< $2,500	$5,000	$10,000	$10,000 - $15,000	$15,000 - $25,000	$25,000 >
Variables	Dependent Variable: Log of Damages					
Log of GDP per capita	1.960***	1.832*	1.701*	1.285*	-1.244***	-1.982*
	(-0.311)	(-1.099)	(-0.98)	(-0.682)	(-0.139)	(-1.087)
Log of Population Density	0.0625*	0.0671**	0.0751***	0.0797***	0.109	0.554***
	(-0.032)	(-0.029)	(-0.026)	(-0.027)	(-0.161)	(-0.195)
Govt. Exp./GDP	0.188***	0.185***	0.065	0.0273***	0.0377***	0.0602
	(-0.01)	(-0.015)	(-0.046)	(-0.004)	(-0.004)	(-0.150)
Risk	0.880**	0.814**	0.209**	0.821**	3.896**	4.466*
	(-0.386)	(-0.351)	(-0.101)	(-0.387)	(-1.912)	(-2.552)
Agriculture Sector/GDP (%)	0.002	0.004	0.004	0.002	0.011	-0.009
	-0.013	-0.007	-0.007	-0.007	-0.019	-0.008
Openness	-0.234**	-0.301**	-0.31**	-0.442*	-0.218	-0.671*
	(-0.112)	(-0.121)	(-0.123)	(-0.263)	(-0.375)	(-0..358)
Polity	-0.029*	-0.034*	-0.057*	-0.022*	-0.011*	-0.347*
	(-0.016)	-0.02	(-0.031)	(-0.013)	(-0.009)	(-0.202)
Constant	7.319	6.04	4.026	2.22	-5.296	21.06
	(-8.205)	(-5.440)	(-5.250)	(-8.703)	(-23.61)	(-22.94)
Observations	331	703	499	106	103	168
Number of Countries	49	77	97	18	16	29

Standard errors in parentheses
*** p>0.01, ** p>0.05, * p>0.1.

The analysis by income bins also confirms that larger shares of government expenditure on GDP have a positive relationship with damages. Interestingly, this is not a characteristic of low income countries (even though the related coefficient is considerably higher for particularly low income countries) but a generalized outcome. This result provides some evidence that larger public intervention in the economy may introduce inefficiency also in the action against disaster related damages.

The risk variable is positive and statistically significant for all the income bins; suggesting that the higher the ratio of those killed to those affected, the greater the impact on climate damages for countries. This is particularly troublesome for relatively poorer countries which have larger population exposed to natural disasters. It is worth recalling that in Table 2 the coefficient for this variable was not statistically significant. One particular reason for this could be the fact that we have fewer observations in the regressions segmented by income class which could be influencing the standard errors. The coefficients for the agricultural share of GDP are also no longer statistically significant.

Increased openness seems to reduce damages from climate disasters across all income levels, further reiterating that increased integration with international trade can be an important damage smoothing component. Estimated results also show that regimes with more democratic qualities have a negative impact on damages, with the effect greater in countries with relatively higher income.

4.3.4 Granger Causality

The analysis conducted in the previous sections highlights indirectly that development, measured by per capita GDP is a driver of adaptive capacity measured by lower damages at least in developed regions. In this section we dig deeper in this relationship. As already noted, it can be argued that the causal relationship between GDP per capita and climate related damages is bidirectional; i.e. damages could determine subsequent income or income could determine subsequent damages. It is also possible to have no interdependency between these two variables.

We test explicitly this link verifying whether per capita GDP Granger causes (lower) damages, if it does then there is further evidence of adaptation. In this case we are not assuming the exogeneity or endogeneity of the underlying variables a priori. GDP per capita Granger causes climate related damages if the lagged GDP per capita helps forecast climate related damages. The standard Granger causality test for time series data is not applicable in the case of panel data and needs to be constructed *ad hoc*. We follow the procedure of Hurlin and Venet (2001) and Hurlin (2005, 2007) allowing more efficiency, control for individual heterogeneity, a reduction in identification problems, modelling temporal effects without aggregation bias present in time series data, and the usual increased robustness due to the use of panel data (Greene, 2008 and Baltagi, 2005).

The Hurlin heterogeneous non-causality hypothesis (HENC) test, verifies the existence of a causal relation in the Granger sense from the variable x to y in some or at least one country in the panel even though the relation is no homogeneous across the entire panel. The linear panel data model can be written as;

$$y_{it} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} \gamma_{(it-k)} + \sum_{k=1}^{K} \beta_i^{(k)} x_{(it-k)} + \epsilon_{it} \tag{4.5}$$

Where $\gamma_i^{(k)}$ and $\beta_i^{(k)}$ are various coefficients of $y_{(it-k)}$ and $x_{(it-k)}$ for country i.

We test the causal patterns for four income groups and the coefficients of each group are tested against the null hypothesis of zero causality i.e. $\beta = 0$. The F_{HENC} test statistic in practice amounts to build an $F - test$ where the sum of squared residuals (SSR) from this restricted regression ($SSR2_{ij}$) is then compared to those from the unrestricted model ($SSR1$);

$$F_{HENC} = \frac{(SSR_{2,j} - SSR_1)/(n_{nc}p)}{SSR_1/[NT - N(1+p) - n_c p]} \tag{4.6}$$

In Equation 4.6, n_{nc} is the subset of countries for which β is restricted to zero, while n_c is the subset of countries for which β is not restricted to zero, N is the number of countries, p is the number of lags, and T is the number of time periods.

A significant F_{HENC} test statistic allows for the rejection of the hypothesis for sub-group j, suggesting that x Granger causes y for that particular subgroup of countries. Thus, if the null is accepted, the variable x does not Granger cause the variable y for all the selected units of the panel. The test, however, requires the variables to be covariance-stationary. Accordingly, Table 4.4 shows first the panel unit root test results of GDP per capita and climate related damages. A Fisher type test for unbalanced panel suggests that both the log transformed GDP per capita and climate damages are non-stationary in levels but stationary when first differences were taken.

Table 4.4: Panel Unit Root Tests for Key Variables

Variables	Fisher Unit Root Test
Log of Damages	3.55
	(-0.99)
Log of GDP per capita	4.18
	(-0.99)
Lagged Log of Damages	-10.15
	(0.00)
Lagged Log of GDP per capita	-14.52
	(0.00)

Note: p-value in parentheses

Hence, we differenced the data for this purpose. Then, in order to conduct the panel Granger non-causality test by Hurlin (2004 and 2005), the requirement is $Ti > 5 + 2K$ (T_i being the time span for country i and K represents the autoregressive lag orders). The panels in our dataset are often relatively short, which limits the degrees of freedom. As a result the analysis is based on $K = 1$. Table 4.5 shows the results from the panel Granger non-causality test between the first-differences of log of GDP per capita and log of climate damages.

Table 4.5: Granger Causality Tests: GDP per capita and Climate Damages with Non-stationarity Correction

Panel	GDP → Damages	Damages → GDP
All countries	0.515	0.596
<$2,500	2.406**	1.365
<$5,000	2.354*	1.248
$15,000 - $25,000	-1.223	0.986
$25,000-$35,000	-1.301	0.898

Note: The panel Granger homogeneous non-causality (HENC) null hypothesis is No Granger Causality.
*** p>0.01, ** p>0.05, * p>0.1.

We find no evidence of changes in GDP per capita Granger causing higher climate damages for the entire panel. However, for countries with GDP per capita below $5,000 increasing GDP per capita seems to Granger-cause higher climate related damages. In other words, for countries at the earlier stage of development, GDP per capita is a driver (in a Granger sense) of damages (and not vice versa). However, the link goes in the opposite direction that one would expect, as growth brings about more damages. This is further evidence of maladaptation or of increased disaster vulnerability at earlier stages of economic development which is brought about by more assets (and population) at risk not yet compensated by sufficient investment in vulnerability reduction. Echoing one of the theoretical justifications of the Environmental Kuznets Curve-like behavior (see e.g. Ruttan, 1971 and Antle and Heidebrink, 1995), it could be argued that protection against weather related disasters is in a way a superior good which enters societal preferences only after more basic needs are fulfilled. For the panel related with income above $15,000, the test statistics are negative, but not statistically significant, suggesting that there is no evidence of increasing GDP per capita Granger causing a reduction in climate related damages. While our regression results suggest that higher income countries are better at improving their adaptive capacity over time, this may not be enough to significantly reduce their monetary damages due to climatological disasters. None of the test statistics in column 2 (Table 4.5) are statistically significant, suggesting that higher damages do not Granger cause the GDP per capita.

4.4 Conclusion

In this paper we have tried to detect the existence of ongoing adaptation or of the working of adaptive capacity against climate related damages by examining a panel combining climate disaster, socio-economic, and climatic data between 1980 and 2012 for 104 countries. The analysis for the entire data set provide evidence of adaptation as suggested by a statistically significant per capita GDP and population density in both the short and the long run.

More specifically, our results suggest that as the income of a country increases, so does damages from climate related disasters but less than proportionately. We call this, adaptation in a *weak form*. We also find some evidence of maladaptation in the short-run. This could highlight either the fact that increase in damages in the last few decades have been driven by greater development and more assets being at risk or that adaptation needs some time to exert its effects (Pielke et al., 2008).

Splitting the sample by income bins we are able to offer a richer characterization of adaptation trends. Namely; higher income countries feature adaptation in a *strong form*, i.e. losses are decreasing with per capita GDP. On the contrary, in lower income countries, damages increase more than proportionally with per capita GDP. This provides empirical evidence that in earlier phases of development more *assets-at-risk* tend to prevail over adaptive capacity, thereby increasing vulnerability to climate change. In perspective, at higher income levels more resources are available and preferences likely shift toward building climate change/disaster resilience. This induces adaptive capacity, which eventually overcomes the *assets-at-risk* effect. Confirming earlier literature results we also show that regimes with more democratic qualities and trade openness are more successful in adaptation and that countries with larger agriculture sector are more exposed. Finally, using a panel data Granger causality test, we provide evidence that increasing GDP per capita Granger causes higher climate related damages in low income countries but not in higher income countries. This further supports the intuition that at earlier stages of economic development more assets are at risk without being sufficiently compensated by investment to reduce vulnerability. This can induce higher economic losses or maladaptation. However, the causalities are not bi-directional - higher damages do not have a statistically significant impact on GDP per capita. This has an immediate policy implication; development per se is not sufficient to grant (climate change) disaster resilience but adaptive capacity needs proactive investment to be improved. This applies particularly to low income countries which may face an increasing vulnerability to climate change impacts as one of the undesired effects of *ungoverned* development. Supporting adaptation in lower income countries thus becomes a further means to channel their development towards a more sustainable path.

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Appendix A

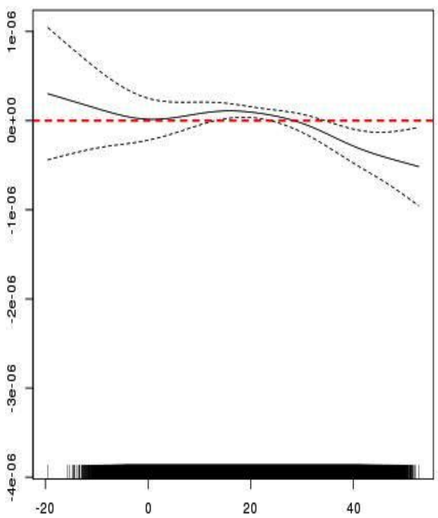
Chapter 1 Appendix

Table A.1: AIC and BIC Test Statistics

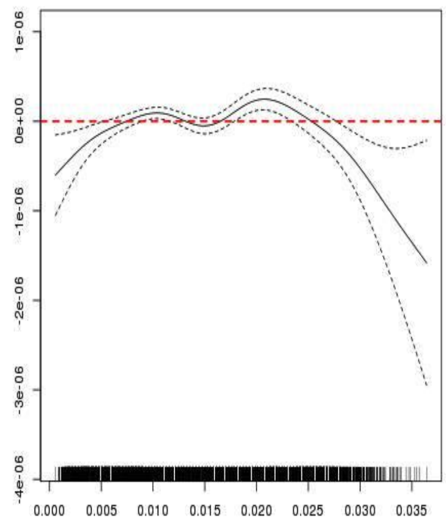
Specification	Dependent Variable Lag(s)	Temperature Lag(s)	Humidity Lag(s)	AIC	BIC
GAM - Min (Year & Week FE)**	No	No	No	-3883625	-3881552
GAM - Min (Year & Month FE)	No	No	No	-3883113	-3881459
GAM - Min (Month & Week FE)	No	No	No	-3881920	-3880147
GAM - Min (Year FE)	No	No	No	-3880787	-3879226
GAM - Min (Year & Week FE)	1	1	1	-3799307	-3797175
GAM - Min (Year & Month FE)	1	No	No	-3785389	-3783740
GAM - Min (Year & Month FE)	1	1	1	-3785402	-3783707
GAM - Min (Year & Week FE)	1	No	No	-3785735	-3783703
GAM - Min (Year & Month FE)	1 - 2	1 - 2	1 - 2	-3686979	-3685246

Figure A.1: GAM Splines - Maximum Temperature and Maximum Humidity

(a) Figure A1.a: Maximum Temperature



(b) Figure A1.b: Maximum Humidity



(c) Figure A1.c: Log of Income

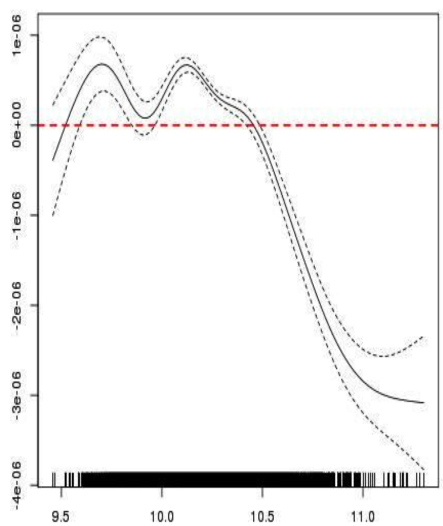
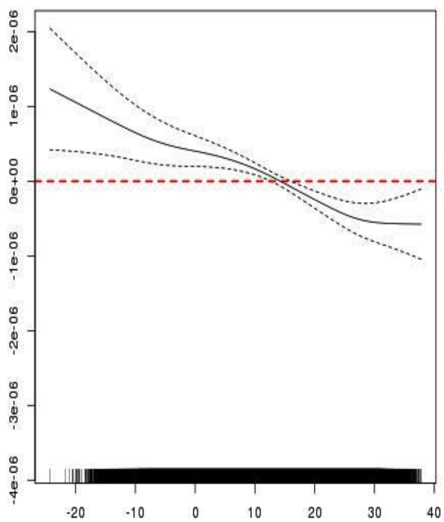
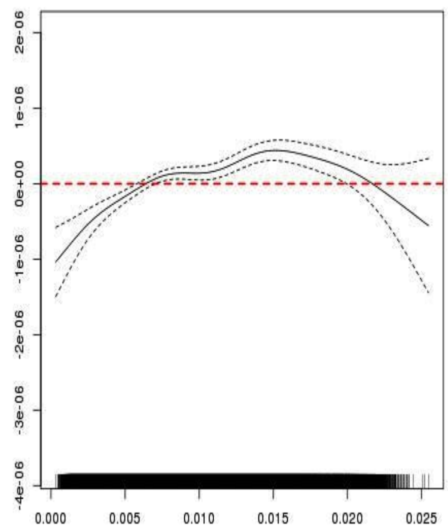


Figure A.2: GAM Splines - Mean Temperature and Mean Humidity

(a) Figure A2.a: Maximum Temperature



(b) Figure A2.b: Maximum Humidity



(c) Figure A2.c: Log of Income

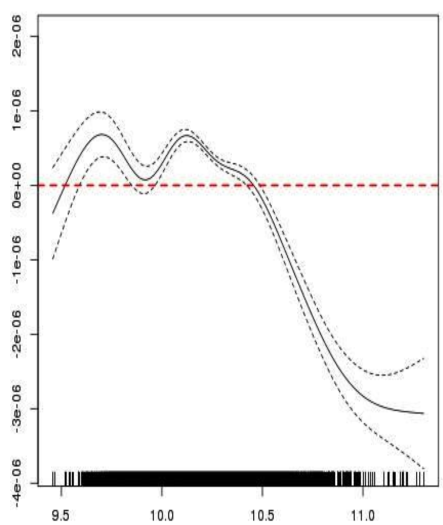
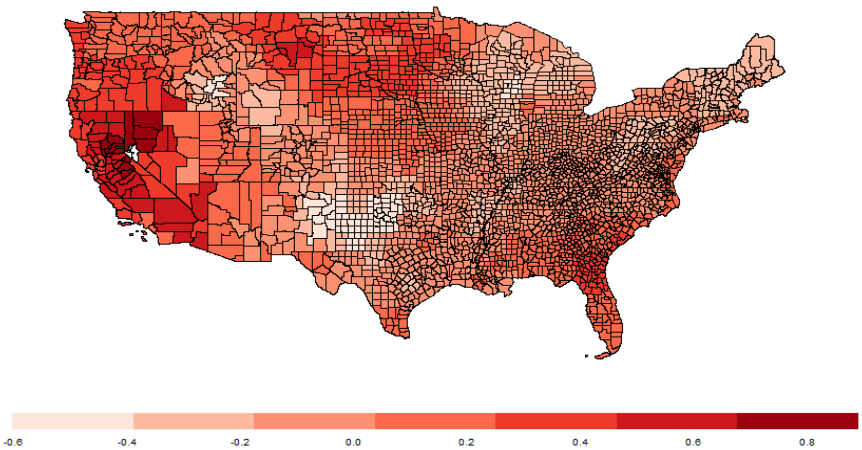
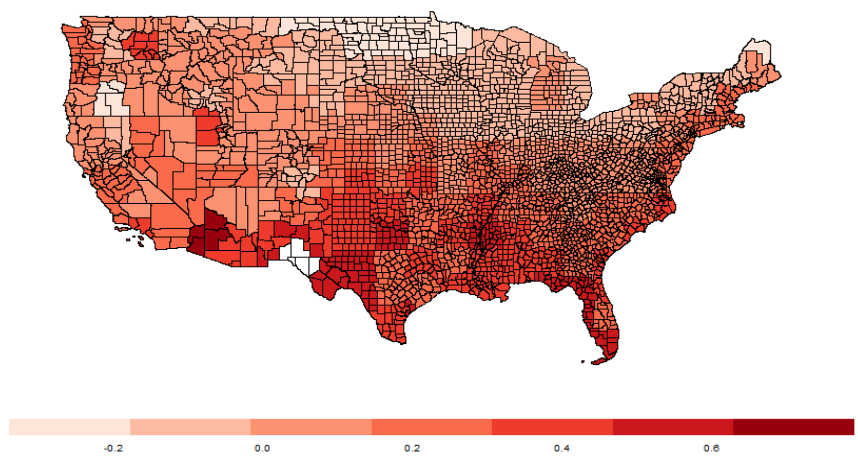


Figure A.3: Projected Change in Influenza Mortality (%): RCP 4.5 (Mid-Century)

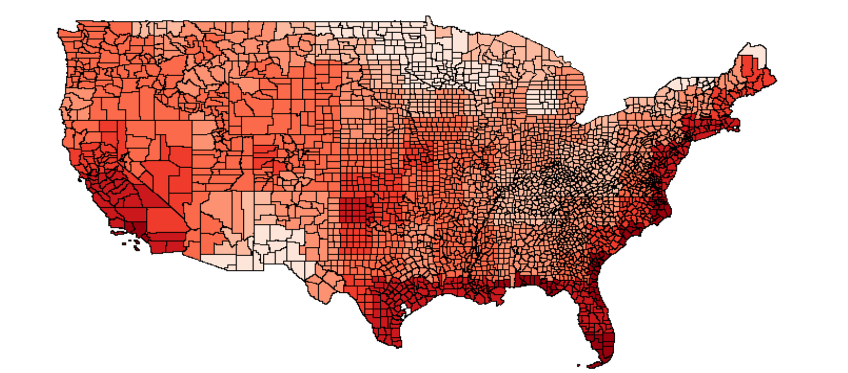
Projections: 2026-2045 (CNRM-CM5: 4.5) using Min GAM



Projections: 2021-2050 (GISS-ER2: 4.5) using Min GAM



Projections: 2026-2045 (NorESM1: 4.5) using Min GAM



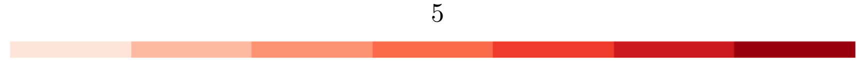
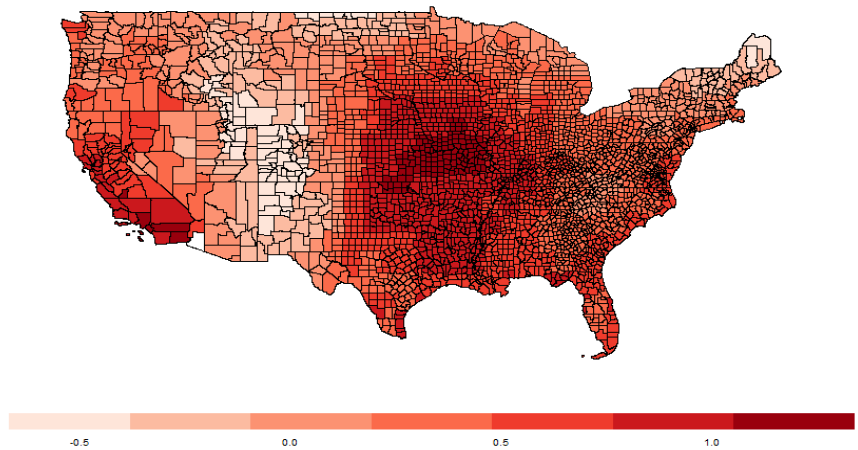
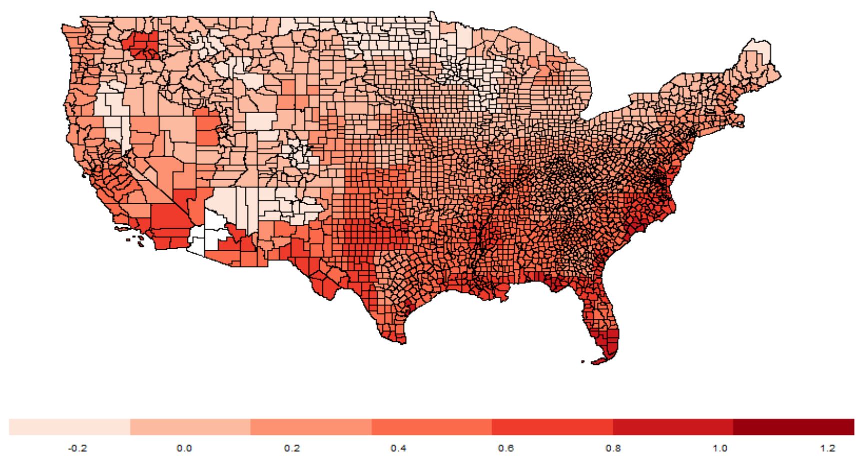


Figure A.4: Projected Change in Influenza Mortality (%): RCP 4.5 (End-Century)

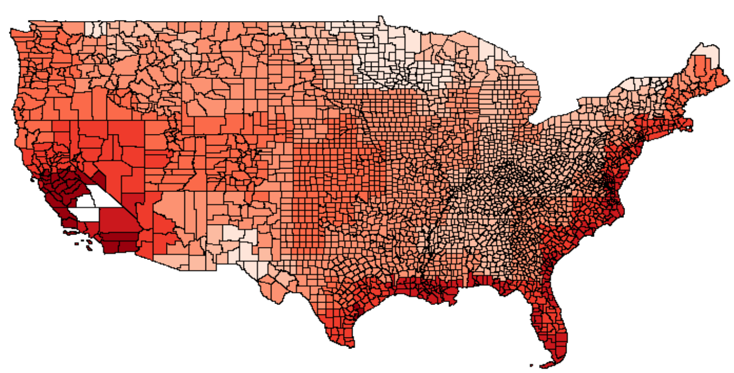
Projections: 2081-2100 (CNRM-CM5: 4.5) using Min GAM



Projections: 2081-2100 (GISS-ER2: 4.5) using Min GAM



Projections: 2081-2100 (NorESM1: 4.5) using Min GAM



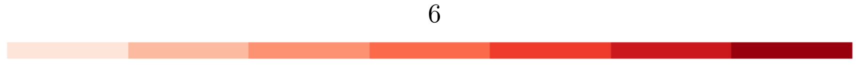
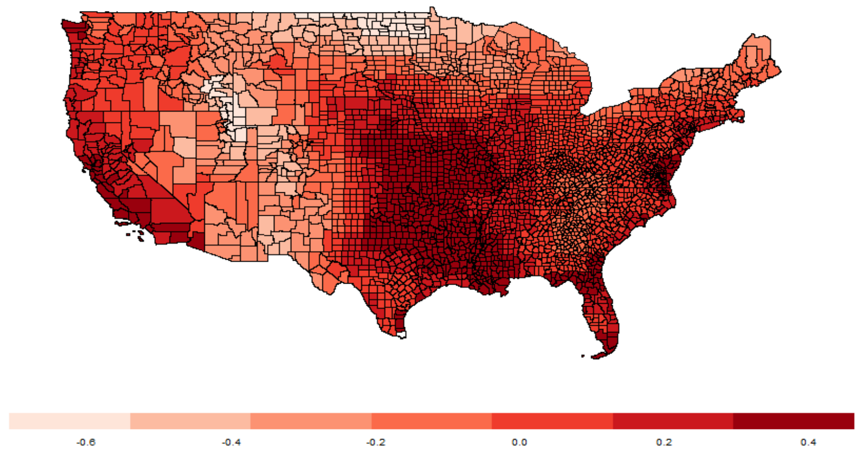
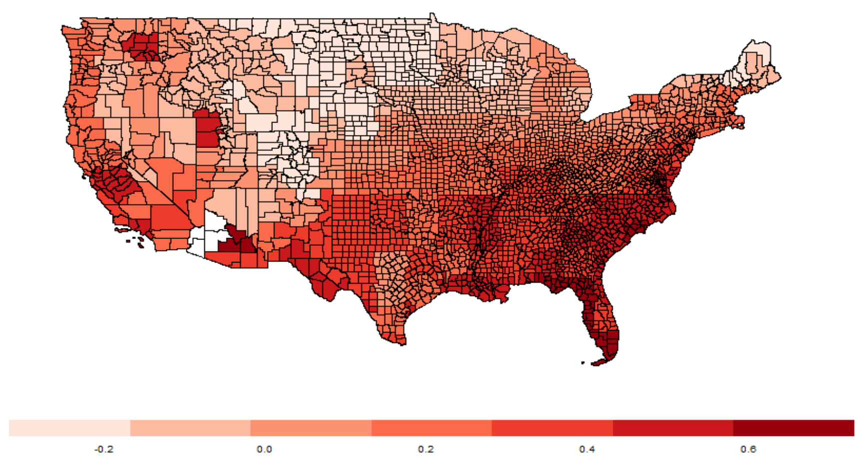


Figure A.5: Projected Change in Influenza Mortality (%): RCP 8.5 (Mid-Century)

Projections: 2026-2045 (CNRM-CM5: 8.5) using Min GAM



Projections: 2021-2050 (GISS-ER2: 8.5) using Min GAM



Projections: 2026-2045 (NorESM1: 8.5) using Min GAM

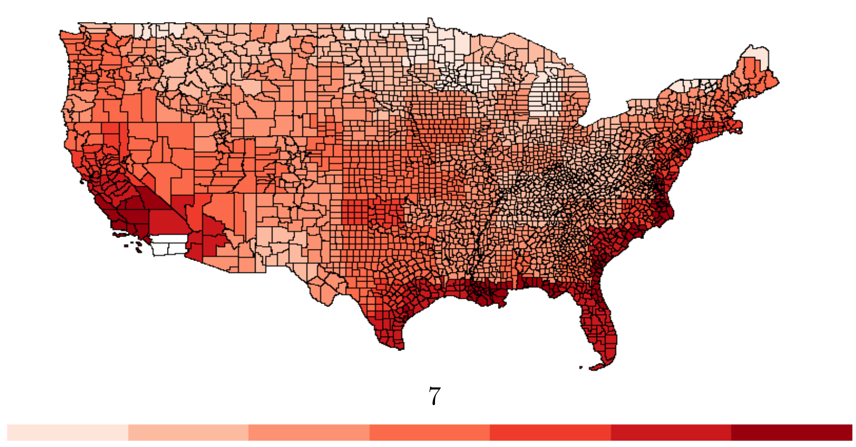
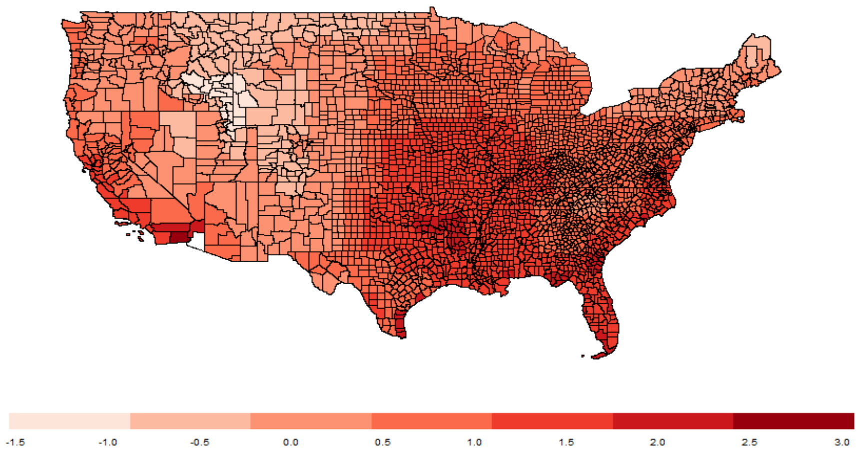
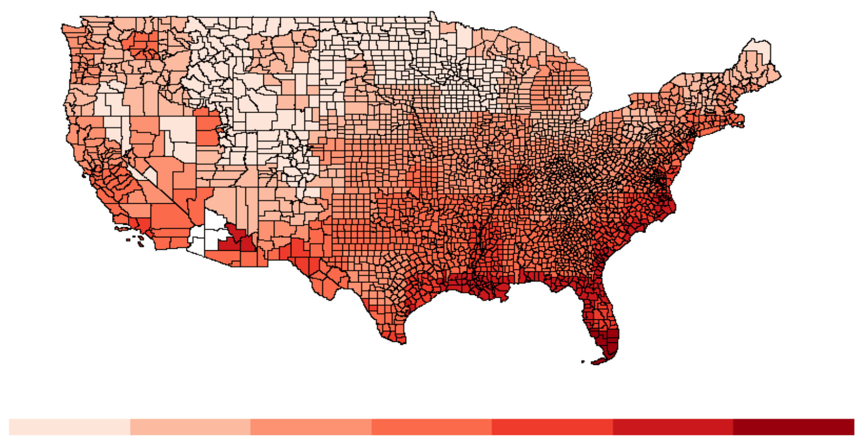


Figure A.6: Projected Change in Influenza Mortality (%): RCP 8.5 (End-Century)

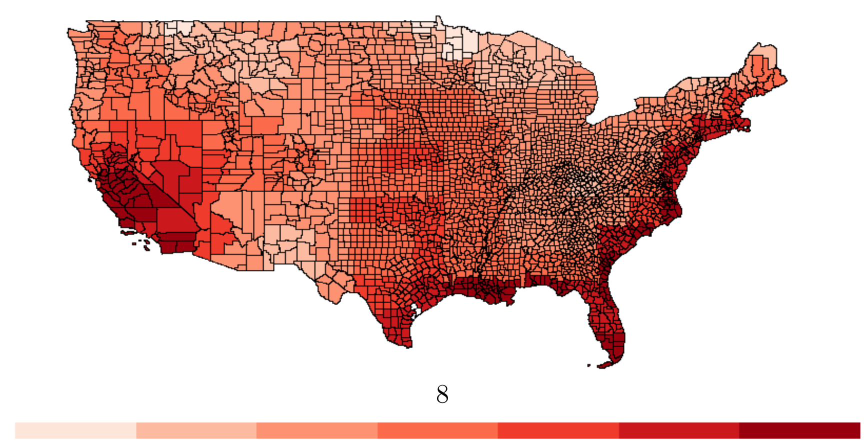
Projections: 2081-2100 (CNRM-CM5: 8.5) using Min GAM



Projections: 2081-2100 (GISS-ER2: 8.5) using Min GAM



Projections: 2081-2100 (NorESM1: 8.5) using Min GAM



Appendix B

Chapter 2 Appendix

Table B.1: Annex I - List of Countries

1	Afghanistan	43	Honduras	85	Sri Lanka
2	Angola	44	India	86	Sudan
3	Argentina	45	Indonesia	87	Suriname
4	Armenia	46	Iran	88	Swaziland
5	Azerbaijan	47	Iraq	89	Syria
6	Bangladesh	48	Kenya	90	Tajikistan
7	Belize	49	Korea, North	91	Tanzania
8	Benin	50	Korea, South	92	Thailand
9	Bhutan	51	Kyrgyzstan	93	Timor-Leste
10	Bolivia	52	Laos	94	Togo
11	Botswana	53	Liberia	95	Turkey
12	Brazil	54	Libya	96	Turkmenistan
13	Burkina Faso	55	Madagascar	97	Uganda
14	Burundi	56	Malawi	98	United Arab Emirates
15	Cambodia	57	Malaysia	99	Uzbekistan
16	Cameroon	58	Mali	100	Vanuatu
17	Central African Republic	59	Mauritania	101	Venezuela
18	Chad	60	Mauritius	102	Vietnam
19	China	61	Mexico	103	Yemen
20	Colombia	62	Morocco	104	Zambia
21	Comoros	63	Mozambique	105	Zimbabwe
22	Congo	64	Myanmar		
23	Congo, the Democratic Republic of the	65	Namibia		
24	Costa Rica	66	Nepal		
25	CĂ´te d'Ivoire	67	Nicaragua		
26	Djibouti	68	Niger		
27	Dominican Republic	69	Nigeria		
28	Ecuador	70	Oman		
29	Egypt	71	Pakistan		
30	El Salvador	72	Panama		
31	Equatorial Guinea	73	Papua New Guinea		
32	Eritrea	74	Paraguay		
33	Ethiopia	75	Peru		
34	Gabon	76	Philippines		
35	Gambia	77	Rwanda		
36	Georgia	78	Sao Tome and Principe		
37	Ghana	79	Saudi Arabia		
38	Guatemala	80	Senegal		
39	Guinea	81	Sierra Leone		
40	Guinea-Bissau	82	Solomon Islands		
41	Guyana	83	Somalia		
42	Haiti	84	South Africa		