ISSN 1833-4474

The Climate Trap of Health Development:
An Empirical Analysis of the Effects of Climate and Income on Mortality

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Abstract

This paper examines the dynamic relationship between climate, health, and income. We partition the effects of climate and income on mortality into the pure climate effect, the pure income effect, and the overlapping effect, and show that African countries exhibit a large pure climate effect but a negligible pure income effect, while non-African countries exhibit the opposite pattern. We provide further empirical evidence that while climate is important in determining both health and income, income can in turn provide a shield against the adverse effects of climate on health. This interaction between climate, income and health can give rise to either a virtuous cycle of prosperity or a vicious cycle of poverty. The findings have important implications in the context of climate change, as global warming is likely bringing about a worsening of climatic conditions in poorer countries that could see many of them sinking deeper into a climate trap of underdevelopment in health.

Keywords: Mortality, climate, virtuous cycle, vicious cycle, development, climate change

JEL Classification: I10, I19, Q56

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1. Introduction

The relationship between climate and health is receiving more attention than ever with global warming emerging as one of the greatest challenges for humankind in the 21st century. This is evident with human health featuring prominently as one of the dimensions to assess the impact-adaptation-vulnerability of climate change in the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC 2007). The concern over human health is rightly justified because although climate change could have some positive impacts on health, such as reduction in cold-related mortality and morbidity, by and large the effects are negative (Confalonieri *et al.* 2007). Even if international action were taken to deal with global warming now, climate change would continue for at least a few decades to come (IPCC 2001). Furthermore, the global nature of climate change means that it is necessary to develop health risk management strategies different from those being used in the past against localized environmental health hazards such as air pollution or water contamination (McMichael et al. 2008). The climate change backdrop aside, assessing the climate-health relationship is an important issue on its own. In particular, the returns to health expenditure (or health interventions) may differ across climate zones, so knowledge of the impact of climate on health can be used to make cross country comparisons of health performance and health system efficiency more meaningful.

Previous research on the health effects of climate and climate change has focused largely on individual effects such as thermal stress (i.e. heatwave or cold-wave), other extreme weather events (e.g. drought, cyclone), and infectious diseases (e.g. malaria, cholera), with some extension to crop production and malnutrition (McMichael et al. 2006; Haines et al. 2006). But there is little research on the social, economic, and demographic disruptions due to climate change and their flow-on effects on health (McMichael et al. 2006). Empirical studies on low income countries are even rarer, despite the fact that low income countries are at much greater risks than high income ones in the face of rapid climate change (Haines et al. 2004, 2006).

Instead of investigating individual climate-sensitive health hazards, the current paper examines the effect of climate on mortality using a large cross country dataset. Cross country datasets are useful in quantifying the difference in mortality that can be attributed to the variation in climatic conditions across countries, and how this effect may be modified by various socioeconomic conditions (e.g. Tang, Chin & Rao 2008). Examining the climate-health relationship is made challenging by a number of factors. Firstly, climate (and geography in general) affects economic development not only through its impact on health but also via agricultural production (Sachs 2001; Masters and McMillan 2001; Gallup et al. 1999).[1] But things are made more complicated as income (along side other positive aspects of development) is also vital in determining health status; therefore, the climate-health relationship should not be examined in isolation from the income-health relationship as the two effects are likely to overlap. Secondly, climate itself is multidimensional, and while a good climate for health may also be a good climate for productivity, this need not be the case. For instance, frost can help kill pests that damage crops as well as parasites that infect human; whereas regular rainfall which is beneficial to crop production can also lead to mosquitoes breeding. Previous studies like Sachs (2001) and Masters and McMillan (2001) focus largely on the tropical-temperate climate zone division. In contrast, the current study

[1] Natural disasters or even regular climatic events can also affect non-agricultural production and other economic activities, e.g. heavy rain could cause transportation interruption.

measures climate using multidimensional parameters. Thirdly, while climate can affect productivity and health, income can in turn provide a buffer against the adverse effects of climate on health and production. The last two factors together imply that the triangular climate-income-health relationship is dynamic rather than static. An innovation of the current study is that it makes use of multiple but related regressions to disentangle this complex relationship, and eventually integrates the findings into a coherent “climate trap” model of development for countries of vastly different health and income levels.

The empirical analysis of this paper is divided into two parts: sections 2 and 3 respectively. In section 2, we use variation partition method (Borcard 2002) to decompose the effects of climate and income on mortality into three components: the pure climate effect, the pure income effect, and the overlapping climate-income effect. The pure climate effect is defined as the impact on mortality that is associated with climate only (i.e. excluding the indirect impact of climate on health via income), the pure income as the impact associated with income only, and the overlapping climate-income effect as the inseparable impact associated with both. The conclusion of this section is clear and distinct: the pure climate effect is close to negligible for non-African countries, whereas the pure income effect is close to negligible for African countries. Further investigation as to what gives rise to such a contradiction is the focus of section 3.

While it may be tempting to attribute the contradiction between the two groups to their differences in climatic and socioeconomic conditions, such a simple explanation has missed the key fact that income and climate need not be independent in their impact on health. In section 3, we examine how the interaction between climate and income can affect mortality using a number of techniques. The findings from various estimations consistently point to the same conclusion: climate impacts on mortality, but higher incomes can moderate this effect. This implies that income is more important in terms of improving life expectancy for countries with less favourable climate for health. These findings leads to the development of a climate trap model in section 4. The model provides a unified explanation of the income and mortality gaps between countries of different climatic conditions. Lastly, section 5 concludes the paper with a further discussion of the implications of our findings in the context of climate change.

2. Empirical Result: Part I

2.1 Partitioning the Effects of Climate and Income on Mortality

In this section, we use the variation partition method to decompose the intertwining effects of climate and income on mortality. The function of the variation partition method is to estimate the fraction of the variation in the explained variable contributed by different explanatory variables (Borcard 2002). The national life expectancy at birth (LE) for the year 2000 is used as the explained variable. Life expectancy is good measure of population mortality because it summarizes the mortality risks of different age and sex groups, and has been used widely for health and wellbeing assessment. In our content, the variation partition method involves estimating three empirical models:

(Climate only)
$$LE_i = \alpha_0 + \sum_{k=1}^{9} \alpha_k \, climate_{k,i} + e_i \qquad (1)$$

(Income only)
$$LE_i = \beta_0 + \beta_1 \, LGDP_i + \varepsilon_i \qquad (2)$$

(Climate and income) $$LE_i = \gamma_0 + \sum_{k=1}^{9} \gamma_k \, climate_{k,i} + \gamma_{10} \, LGDP_i + u_i \qquad (3)$$

where i is a country index; k is a climate variable index; and e, ε and u are error terms. In model (1), there are nine explanatory variables which capture various aspects of the climate for a particular country. They include: mean distance to coast in km (DNEW_POP); mean elevation in km (EMEAN_POP); mean standard deviation of elevation in grid cell (ESD_POP);[2] roughness of elevation in grid cell (ROUGH_POP);[3] a dummy for being landlocked (LANDLOCKED); average monthly temperature in Celsius (TEMPAV_POP); standard derivation of temperature (TEMPSD_POP); average monthly precipitation in mm (PRECAV_POP); standard deviation of monthly precipitation (PRECSD_POP). The first four variables are included here because they are relevant to seasonality. Admittedly they could have wider biophysical relevance than just climate. But these biophysical factors are also important in determining the effect of climate on human health. For instance, population that live close to seashore will be more affected by wind storm and change in sea level, while those live at high attitude will have less access to health care. The data are sourced from GEon 1.3 database (see the Appendix for details). The variables are weighted by population distribution within countries with a resolution up to the size of a grid cell. This adjustment is essential for countries that have very different climates in different territorial regions, especially large countries. In Australia, for

[2] One grid cell is of the size one-degree latitude by one-degree longitude, approximately equal to 100km by 100km.

[3] The difference between roughness and standard deviation of evaluation is that, the former measures the “mountainousness” of a grid cell. For details of the estimation method, see Hood (2005).

example, most of the population lives in temperate climates near the coastline, large inland areas with hostile climate are mostly uninhabited.[4]

Model (2) has a single explanatory variable – log income per capita measured in purchasing power parity, constant 2000 international dollar terms (LGDP). To mitigate the reverse causality from income to mortality, we use the average value of income per capita from 1990 to 1999. The average is preferred to a single year value as it is less likely to be affected by country specific business cycles. Model (3) includes both the nine climate variables and the log income per capita variable as explanatory variables. Models (2) and (3) are noticeably parsimonious on non-climate determinants with only income per capita included. This is because income per capita is a strong proxy for socioeconomic development and is highly correlated with many other development indicators. These exclusions also simplify the model so we can concentrate on the health effects of climate and income. On the contrary, a large number of climate variables are included in the models because the relationships between climate and mortality and between climate and income are unlikely to be unidimensional.

Table 1 reports the results of three regressions for the full sample of 152 countries. Based on the coefficient of multiple determination or simply goodness-of-fit statistic

[4] Besides average and standard deviation, the database also provides information on maximum and minimum temperature and precipitation. However, the standard deviation and average temperature/precipitation explain nearly all of the variation across countries in terms of minimum and maximum temperatures/precipitation. Including these variables tends to render the average and standard deviation measures insignificant, and adds very little to the model in terms of explanatory power.

(R^2), even a single explanatory variable LGDP can explain nearly 65% of the variation in LE in the full sample; including the climate variables pushes that up to 80%. It proves that in the content of cross country regression, these parsimonious models have high explanatory power.

The R^2 statistics are analysed in order to disentangle the intertwining effects of climate and income on mortality, as depicted in the Figure 1. In this Venn diagram, the overlapping part represents the indirect effect of climate on mortality via its effect on income. This is because the alternative interpretation that a country's income can affect its climate is implausible, at least in the short term. On the contrary, the pure climate effect represents the effect of climate on mortality via pathways unrelated to income, such as heatwaves or climatic conditions that foster the spread of disease. Similarly, the pure income effect represents the income component that is unrelated to climate, such as institutional quality or government policies. The R^2 statistic measures the variation of the dependent variable that is explained by the independent variables; therefore the more important climate is in determining mortality, the greater the R^2 of the model (1); the same for income per capita in model (2). Thus, the R^2's of models (1), (2), and (3) provide measures of the explanatory power on mortality of the total climate effect, the total income effect, and the combined climate and income effect. Here we can impute the size of the pure climate effect by subtracting the total income effect from the combined effect: 0.800 – 0.639 = 0.161. Similarly, the pure income effect can be calculated as 0.800 – 0.651 = 0.150, and the overlapping effect as 0.639 + 0.651 – 0.800 = 0.490. In order to measure the relative importance of each factor, we normalize the combined effect to 100%, then the pure clime effect, the pure income effect, and the overlapping effect will be roughly equal to 20, 20, and 60% respectively. The figures are summarized in Figure 2 (the “All countries” bar).

2.2. African and non-African countries

Since in general African countries have harsher climates and worse mortality records than the other countries, we separate them out in model 3 using an African dummy.[5] (Note for reviewers and editors: All the results not reported in the paper will be made available to readers on requests and are shown in the Appendix 2.) An F-test shows that the terms involving the African dummy are jointly significant (p-value=0.00). This suggests that African and non-African countries should be modelled separately. Table 1 reports the results for the split samples of 113 non-African countries and 39 African countries (suffix “NA” denotes the non-African sample and “A” for the African one).[6] Although the level of significance for the climate variables for the two sub-samples is not as high as that of the full sample, an F-test shows that at least one coefficient of the climate variables is significant at the 1% level for the African sample (p-value=0.00) and at the 5% level for the non-African sample (p-value=0.02).

The decompositions of the pure climate effect, the pure income effect, and the overlapping effect for the two sub-samples are shown in Figure 2. The two sub-samples give very different results. For African countries, the pure income effect is of a negligible size at 3%, while the pure climate effect is much larger at 66%. Non-

[5] Detail results are not shown to save space. All detail results not reported in the paper can be obtained from the authors on request.

[6] We do not further separate sub-Saharan African countries out because that will render the sample size to be too small.

African countries have a converse result in that the pure climate effect is less than 5% but the pure income effect is close to 40%. We can rule out the possibility that this contradiction is due to differences in income and climate variations between the two samples. This is because, if anything, income variation is larger in the African sample and climate variation is larger in the non-African sample (Table A1, Appendix). The contradiction between the two groups will be further examined in detail in the next section. Nonetheless, we would like to point out upfront that caution must be exercised in placing too much emphasis on the quantitative results from the African sample. This is because firstly the African sample is rather small; secondly many African countries are plagued with HIV/AIDS epidemics; and thirdly mortality data for African countries are notoriously poor. Since the non-African sample is of much better quality data, in what follows we will use it as the main vehicle to investigate the interacting mechanism between climate and income, and we return to the African sample later to confirm whether the same mechanism is applicable there.

3. Empirical Results: Part II

3.1. Climate-income interaction

To investigate how climate interacts with income in affecting mortality, we again conduct a number of regression analyses. Each of the techniques involved has its own advantages and disadvantages, but together they provide a powerful tool to scrutinize the robustness of the findings.

In the first analysis, we examine if the impact of climate on mortality changes with income level. To this end, for model 3A we split the non-African countries into two groups at the median income level at 6000. An F-test for the null hypothesis that the coefficients of the climate variables are the same across both samples is rejected (p-value=0.03), indicating that the effect of at least one climate variable on health is different for the two income groups. This suggests that income level may play a role in shaping the effect of climate on mortality. This effect is not induced by potential differences in the effect of income on mortality for each sample as we cannot reject the hypothesis that the coefficients of LGDP are the same across the two samples (p-value=0.93).

To further investigate the above hypothesis, in the second analysis we allow LGDP to interact with each climate variable:

$$LE_i = \delta_0 + \delta_1 LGDP_i + \sum_{k=1}^{9} \phi_k \; climate_{k,i} + \sum_{k=1}^{9} \sigma_k \; LGDP_i \times climate_{k,i} + v_i \qquad (4)$$

The results are reported in Table 2 (model 4NA). An F-test shows that at least one of the interaction terms affects life expectancy (p-value=0.02). Moreover, without exception, the coefficients of each climate variable (ϕ_k) and its interaction term (σ_k) are of opposite signs. This strongly suggests that income can moderate the effects of climate on mortality. Since income is expressed in logarithmic terms, the moderating effect of income diminishes as income goes up.[7] To examine if income moderates the effect of each of the nine climate variables to a similar extent, we conduct an F-test with the null hypothesis that $\phi_1 / \sigma_1 = \phi_2 / \sigma_2 = ... = \phi_9 / \sigma_9$. The result shows that we

[7] Still, the logarithmic function of income per capita does not fully account for the pace at which the moderating effect diminishes. When we include LGDP-squared in the regression, both as a stand alone term and as an interaction term with climate variables, each of the LGDP-squared terms is significant and of an opposite sign to its corresponding LGDP term. This indicates that the moderating effect of income diminishes slower and thus lasts longer before complete depletion than what the logarithmic function suggests.

cannot reject the null hypothesis (p-value=0.66). This result provides a foundation to conduct the third analysis.

In the third analysis, we restrict the moderating factor of income λ_2 to be the same for all climate variables:

$$LE_i = \lambda_0 + \lambda_1 LGDP_i + \sum_{k=1}^{9} \pi_k \, climate_{k,i} + \lambda_2 \left(\sum_{k=1}^{9} \pi_k \, climate_{k,i} \right) LGDP_i + w_i \qquad (5)$$

The result (model 5NA, Table 2) shows that the coefficient of moderating factor (i.e. λ_2) is negative and significant (p-value=0.00), suggesting that as income goes up the effect of unfavourable climate on mortality declines. However, climatic conditions can also impact upon a countries income, so in order to prove that the above result in not an artefact of this causal effect of climate on income we conduct the following analysis.

In the fourth analysis, we first regress LGDP against the nine climate variables using the full sample.[8] The fitted value of LGDP from the regression, LGDP_FITTED, is the income component that is related to climate, and the residue of the regression, LGDP_RESIDUE, is the income component that is unrelated to climatic conditions. In model 6NA, Table 2, we examine if the two components interact with climate in a similar way by interacting each of them with the climate variables. It is found that, like LGDP, both income components have a negative sign. The size of the coefficient of LGDP_RESIDUE is about 2.2 times that of LGDP_FITTED. However, an F-test shows that the null hypothesis that the two coefficients to be same can not be rejected

[8] The reason why we use full sample here will become clear in section 3.2 (see footnote 12).

at the 10% level (p-value=0.14).[9] So, it is safe to conclude that potentially both income components can moderate the effect of climate on mortality, and the effect of the independent income component is at least as large as that of the one associated with climate.

3.2. African countries once again

Do the results in the previous section hold for African countries as well? In principle, the analyses could be repeated using the African sample. However, the small number of observations of the African sample (39 in total) means that using a large number of interaction terms in a regression like model (4), is not practical. Therefore, we only estimate the other two models for the African sample and the results are also reported in Table 2. Just like in model 5NA, the coefficient of the interaction term in model 5A is significant at the 1% level and has a negative sign. When we split the income variable into two components in model 6A, both components retains the negative signs. Although both LGDP and the interaction term of LGDP_RESIDUE are individually insignificant, they are jointly significant at the 5% level (p-value=0.04).[10] Furthermore, the moderating effect of LGDP_RESIDUE is smaller than that of LGDP_FITTED, with the coefficients of the former about one-third the size of the later. This is in contrast to the results for the non-African sample.

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[9] LGDP_FITTED and LGDP_RESIDUE are obtained from a regression using the full sample. If we re-estimate them using the non-African sample and use the new income components measures in model 5NA, the results remain largely the same.

[10] Recall that the fitted value and residue are estimated using the full sample. Using those estimated from the African sample leads to convergence problem during the estimation process.

Overall, some cautious conclusions can be drawn. On the one hand, as reflected in the signs of coefficients, the mortality of African countries are subject to the forces of climate and income in a way *not dissimilar* to their non-African counterparts. On the other hand, as reflected in the magnitude and significance of the coefficients, the strength of these forces may not be the same across the two samples. However, further investigation is needed to verify the second point.

3.3. HIV/AIDS

The analysis of the African sample is made difficult not only by the small sample size, but also the fact that most African countries are of high HIV/AIDS prevalence, as compared to an average non-African country. Since in general the climate of African countries is quite distinct from that of non-African countries, the very large pure climate effect evident in the African sample could be a result of its high HIV/AIDS prevalence.

We have experimented with a number of methods to control for HIV/AIDS. The most direct method is to include a HIV/AIDS prevalence variable in all the regressions. However, the recently renewed HIV/AIDS data compiled by the World Health Organization only cover 2005, leading the LE data by five years. Using these data will invoke endogeneity problems. This is because HIV transmission is often considered to be related to the current level of life expectancy (Mahal 2001), and therefore those countries with low life expectancies are more likely to have a high future prevalence of HIV/AIDS.

The second method is to separate countries of low and high HIV/AIDS prevalence. In Figure 2, we report the decomposition results for countries of HIV/AIDS prevalence of less than and bigger than 1% of the population, respectively. The result for the low prevalence sample is similar to that of the non-African sample, while that for the high prevalence sample is similar to that of the African sample. This is not surprising as African countries dominate the high prevalence sample. Further separating low and high prevalence countries amongst African and non-African countries would leave each group with too few observations for estimation.

The third method is to use life expectancy data from the 1970s as a robustness check, as HIV/AIDS had not yet become an epidemic then. Due to the restriction of data availability, we use 1982 data for life expectancy at birth and 1977 data for income. The results are also reported in Figure 2. For African countries, the results are very similar to those of year 2000. In particular, the size of the pure climate effect is very large and that of the pure income effect is very small. This gives us confidence that our key findings regarding the mortality effects of climate, income, and their interaction, are very robust despite the presence of HIV/AIDS amongst African countries. The result for non-African countries will be discussed in the next section.

4. The Climate Trap Model of Development

4.1 Virtuous and vicious cycles

A consistent finding from all the analyses in section 3 is that income can not only improve life expectancy directly, but can also effectively moderate the impact of climate on mortality. This finding is in line with expectations that countries of higher income level can afford putting more resources to alleviate the adverse effects of climate on health. The alleviation may range from using air conditioners/heaters during summers/winters to using vaccines against tropical diseases, from building storm drainage networks against floods to developing water-recycling systems against droughts. On the other hand, income (or economic development in general) affects mortality positively via the provision of shelters, health services, education, law and order, and infrastructure, and negatively via the pathways of poor diet and lifestyles, urbanization, workplace hazards and stress. So it is reasonable to expect that climate has limited role to play in this process. The finding helps explain the result in Figure 2 that the relative size of the pure climate effect for non-African countries is small while that of the pure income effect is large. This is because, on the one hand, as the effect of climate is largely neutralized by that of income, climate will have little residual impact on mortality; on the other hand, as income not only alleviates health conditions caused by climatic conditions but also improves health conditions unrelated to climate, it has a substantial amount of independent impact on mortality.

The finding that the component of income that is associated with climate can in turn moderate the effect of climate on mortality has important implications. Consider two continents: F(avourable) and U(nfavourable). Suppose initially the income levels of both continents are roughly the same at the subsistence level, but the climate condition in continent F is somewhat more favourable for agricultural production than that in continent U. For instance, continent F has more frost days that help kill parasites (Masters and McMillan 2001). The faster economic growth leads to a higher income level in continent F and thus affords it more resources to reduce mortality risks, including those related to climate. A higher life expectancy will lower the subjective discount rate of non-myopic individuals. Lower subjective discount rate will encourage saving and investment in both physical and human capital, which in turn will stimulate technological progress and eventually higher income growth. A higher income will further alleviate the residual effect of climate on mortality (probably at a diminishing rate). A virtuous cycle is formed. Furthermore, as manufacturing and service sectors grow at the expense of the agricultural sector, it will further mitigate the effect of climate on development and hence mortality. This again explains why in Figure 2 the relative size of the pure climate effect amongst non-African countries is so small.

For continent U, the less favourable climate means that its initial economic growth is low. Without sufficient resources, it cannot afford to develop technology in order to shield its population from the adverse effects of the climate. As long as the mortality rate is high, people have little incentive to save and invest. Consequently, income level remains low and the continent continues to be vulnerable to the adverse climate. A vicious cycle is thus formed. Moreover, since the economy is dominated by agricultural production at this development stage, the income level is closely tied to climate. Thereby, the relative size of the pure income effect, which is independent of climate, is negligibly small.

This climate trap model is further verified with the data of the 1970s. The results in section 3.3 show that, from the 1970s to 1990s there is a substantial increase in the pure income effect at the expense of the pure climate effect (and to a much less extent the overlapping effect) for non-African countries. During the two decades, income per capita of non-African countries has increased by 30% on average. The rise in income level, according to our model, will further moderate the effect of climate on mortality. Therefore, it is logical to see that the size of the pure income effect increases while that of the pure climate effect declines. Moreover, as these economies are increasingly less vulnerable to climate, the direct effect of climate via the income channel should also reduce, as reflected in the reduction of the climate-income overlapping effect over the two periods. For African countries, income levels basically stagnated during these two decades (mean value increases by 3% while median value decreases by 4%). This indeed is consistent with the vicious cycle scenario that, countries inside a climate trap could remain vulnerable to climate for a prolonged period. Admittedly, this consistency does not exclude the possibility that other factors such bad policy could also attribute to the development sluggishness of these countries.

4.2 A Generalized Climate Trap Model

The African and non-African division is a highly simplified, dichromatic spatial view of the world. Climate is not uniformly unfavourable across the African continent, neither is it uniformly favourable across non-African countries. Moreover, a climatic condition that is favourable for health is not necessary equally favourable for (agricultural) production, and vice versa. To further generalize the climate trap model, we propose to classify climatic conditions according to whether they are “good”, “neutral”, or “bad” for health and for production respectively. This generates a total of nine combinations of climatic conditions. Obviously the “good for health and good for production” climatic condition is most favourable for development as they have positive effects on both human capital and productivity. The virtuous cycle effect will be at its full strength in this case. On the opposite, the “bad for health and bad for production” climatic conditions is the most development repressing as the vicious cycle effect will be the strongest then. The other sets of climatic conditions are somewhere in between. Whether a virtuous cycle of prosperity or a vicious cycle of poverty will be formed depends on which of the two climate effects dominates.

To obtain an overall picture of how countries distribute amongst these nine stylized climatic conditions, we construct two climate indexes for 177 countries, one for health and the other for production.[11] The health/production climate index indicates how favourable a country's climatic condition is as far as health/production is concerned. Each index is constructed as a weighted sum of the nine climate variables. The weightings are obtained from regressions. The health climate index is constructed using the estimated coefficient from model (4) except that it is now estimated using both African and non-African countries, but excluding those in war:

$$\textit{Health climate index}_i = \sum_{k=1}^{9} \hat{\phi}_k \ \textit{climate}_{k,i} \tag{6}$$

For production climate index, it is constructed from a similar regression:

$$LGDP_i = \theta_0 + \sum_{k=1}^{9} \theta_k \ \textit{climate}_{k,i} + \theta_{10} LE1982_i + \varpi_i \tag{7}$$

$$\textit{Production climate index}_i = \sum_{k=1}^{9} \hat{\theta}_k \ \textit{climate}_{k,i} \tag{8}$$

where ϖ is an error term, and life expectancy at birth at 1982 (LE1982) is included in (7) to control for initial health conditions.

Figure 3 shows a scatter plot of the two indexes. The solid lines inside the figures indicate the mean values of the indexes, and the shade indicates the ± 0.5 standard deviation bands around the means. If we denote a climatic condition as "good/bad" when the climate index is bigger/smaller than the sample mean by more than half of one standard deviation, then we can identify sets of countries outside the shade in

[11] We can construct indexes for more than 152 countries because, for instance, once we obtain the weights for the health climate index, we can apply them to countries with climate data but without income per capita data.

Figure 2 as those with climatic conditions that are either good or bad for health and production respectively. If the generalized virtuous/vicious cycle theory remains valid, we would expect to see countries with climatic conditions that are good for both health and production being largely of a high income level, where those with climatic conditions that are bad for both being largely of a low income level, and countries with mixed climate conditions registering a mixture of income levels.[12]

Table 3 reports the countries that fall into the 4 categories of climatic conditions. Countries with climate bad for both health and production are all low and lower-middle income countries with the exception of Chile and Costa Rica.[13] African countries make up more than half of the group. On the contrary, countries with climate good for both health and production are slightly more diversified, with European OECD countries make up about one-third of the group. Many of the remaining members of this group are upper-middle or high income countries, with the exceptions of Algeria, Moldova, Tunisia and Ukraine. The group with climate good for production but bad for health has a mixture of countries with both high and low incomes. So for the group as a whole, there is no clear evidence which climate condition dominates the other. In comparison, the group with climate good for health but bad for production are dominated by low and lower-middle income countries, and many of them are in the central Asian regions. So it seems to suggest that for this

[12] It should be pointed out here that even though regression (7) involves LGDP, it does not imply that the constructed production climate index will be highly correlated with LGDP. The correlation between LGDP and the production and health climate indexes are respectively equal to 0.53 and 0.36 only.

[13] The index values of both countries, especially Chile, are indeed fairly close to the one standard deviation bands around the means. Chile falls in this climate category mainly because it has a high elevation and is mountainous.

group, the unfavourable climatic conditions for production tend to dominate the favourable climatic conditions for health. Overall, the distribution of countries amongst the four distinct categories of climate shows support to the generalized climate trap model.

5. Discussion and Conclusion

Malaria is a constant reminder of the impact climate could have on health and development. According to the World Health Organization (WHO), every year more than 500 million people become severely ill with malaria, mostly in sub-Saharan Africa, and the disease causes an average loss of 1.3% annual economic growth in countries with intense transmission. The disease affects people not only via its direct effect on their health, but also indirectly via its effect on their health expenditure, ability to work and to learn. And climate change is expected to raise the number of people vulnerable to malaria in the region dramatically (McMichael et al. 2008). Obviously malaria or infectious diseases in general is not the only pathway through which climate impacts upon health; heatwaves, cyclones, floods, and droughts are some other commonly mentioned pathways. The growing concerns about global warming rightly put the climate-health relationship at the centre in the assessment of the impact-adaptation-vulnerability of different regions to climate change.

The current study represents an effort toward a better understanding of the climate-health relationship in the boarder content of development. The study acknowledges that the effect of climate on health is contingent on socioeconomic conditions and thereby analyses the climate-health relationship in conjunction with the climate-income and income-health relationships. The econometric methods developed in this paper allow us to decompose the effects of climate and income on health into three components: the pure climate effect, the pure income effect, and the overlapping effect. A further investigation of the difference between African and non-African countries leads to a conclusion that, while climate can impact on both health and income, income in turn can moderate or neutralize the effect of climate on health. All these findings precipitate into the “climate trap” model of development.

The findings have important policy implications in relation to climate change. First of all, climate change, such as rise in the average temperature and change in rainfall pattern, is likely to lead to worse climatic conditions for health and production. Our findings suggest that, such worsening of climatic conditions could have very different effects on developed and developing countries. Developed economies with sufficiently high level of income can largely shield themselves from such adverse effect of climate change, while developing countries whose health and economic activities are still vulnerable to harsh climatic conditions are likely to bear the largest burdens. Moreover, the initial health status is an important in determining how fast a population can adapt to a changing climate. Countries that are burdened with diseases and disability will be affected by climate change more than otherwise would be (Confalonieri *et al.* 2007: 406). This means that further deterioration of climatic conditions would result in the poorest countries sinking deeper into the climate trap with little future prospect in finding their way out.

The ability for humankind to adapt to climate change is a crucial element in determining the knock-on effect of global warming on health and development. The moderating effect of income on climate, as identified in our empirical analysis, highlights the great adaptability of humankind to climate-related health hazards. But adaptability does not come automatically; skill and knowledge, awareness, resources and policy are important elements in creating this adaptability. For countries that are currently outside but close to the rim of a virtuous/vicious cycle, policies could play a big role as they may tip the balance of the natural effects of climate on health and production, and set the course of long term development in one way or the other. By knowing the distribution of countries based on the climatic effects on health and production, we can identify (mostly developing) countries that are at the risk of falling into a vicious cycle. This is the first step in developing informed adaptive strategies to alleviate the health risks of climate change. Furthermore, our findings indicate that the impact of climate on health and production are not necessarily correlated. With limited resources, it raises an issue of what specific intervention, or what combination of interventions on health and production will be most cost efficient in promoting development. For example, countries which have good climates for productivity but bad climates for health may benefit in particular from health interventions which offset the impact of climate on health rather than interventions to increase productivity.

Technology is yet another important factor in moderating climate-induced health and production hazards. However, technologies in crucial areas, especially health and agriculture, are ecologically specific and therefore cannot be easily shared between countries with different ecological environment (Sachs 2001; Gollin, Parente & Rogerson 2002). This implies that technological advancement in rich countries, which mostly locates in temperate and coastal zones, do not necessarily benefit poor countries in tropical and landlocked areas. A corollary is that the mortality gap between rich and poor will be further enlarged if there is no deliberate, international effort to put resources into developing technology suitable for the poor countries' ecological environment.

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Figure 1 Effects of climate and income on mortality

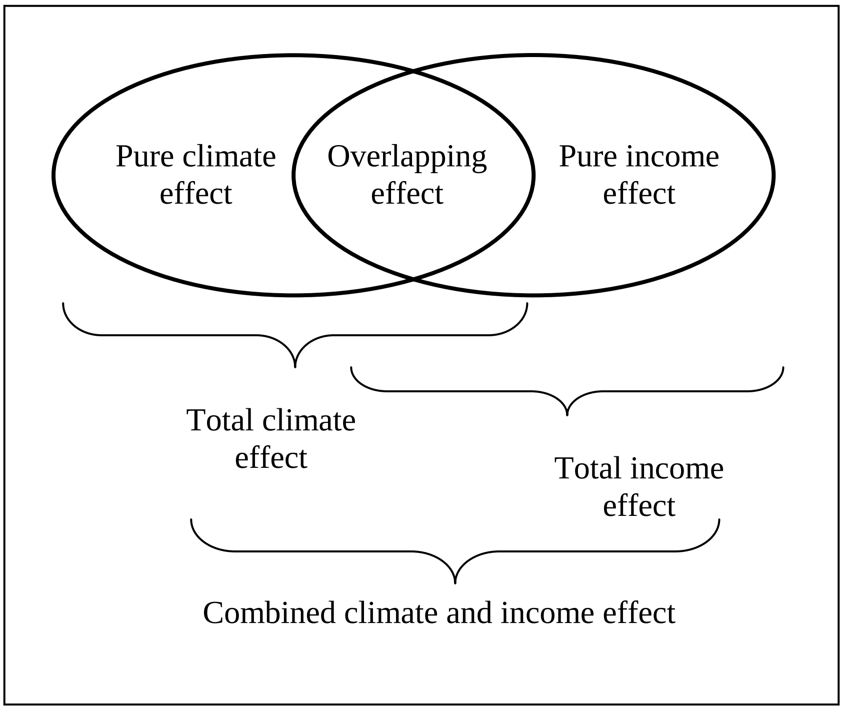


Figure 2 Decomposition of the Effects of Climate and Income on Morality

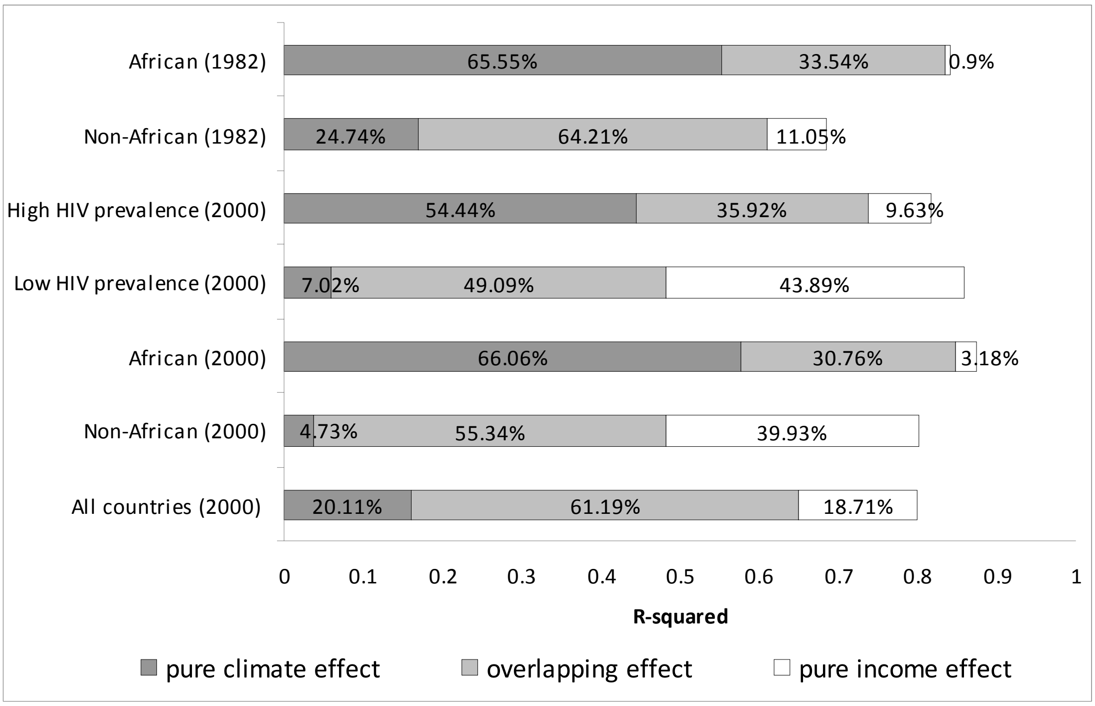
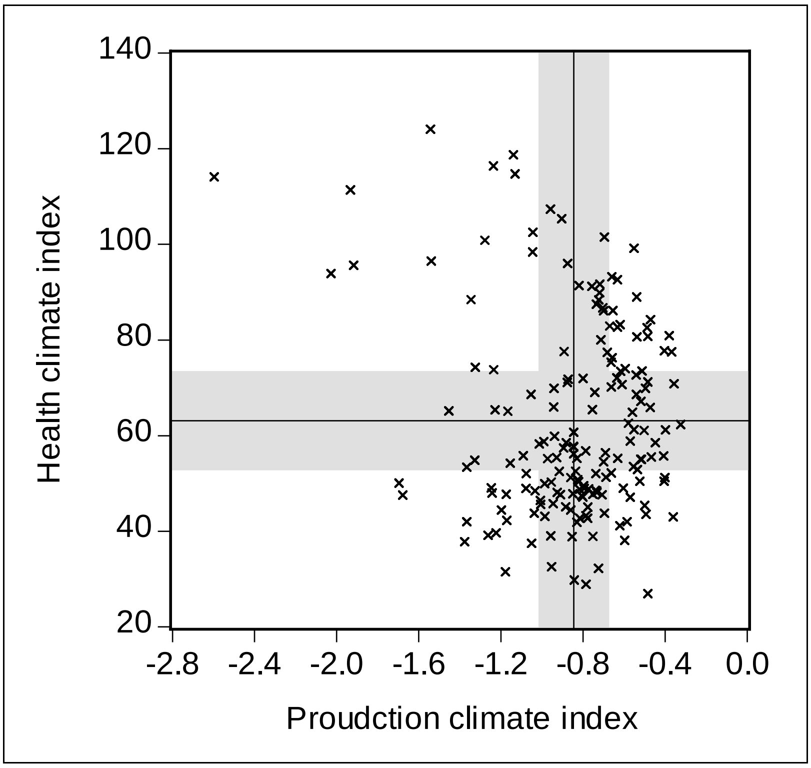


Figure 3 A Scatter Plot of Health and Production Climate Indexes for 177 Countries



Note: The solid lines inside the figure indicate respectively the mean values of the two indexes; the shade indicates the bands of mean ± 0.5standard deviation.

Table 1 Regression results of models 1-3 for the full, non-African, and African samples

	Full sample (no. of obs. = 152)			Non-African sample (no. of obs. = 113)			African sample (no. of obs. = 39)		
	Model 1	Model 2	Model 3	Model 1NA	Model 2NA	Model 3NA	Model 1A	Model 2A	Model 3A
CONSTANT	72.162 ***	-2.529	12.760 **	84.326 ***	21.168 ***	26.155 ***	82.076 ***	3.079	54.910 ***
	(3.554)	(3.928)	(5.900)	(3.086)	(3.001)	(5.986)	(16.214)	(12.195)	(17.943)
DNEW_POP	-0.010 ***		-0.003	-0.006 ***		-0.002	0.005		0.008
	(0.002)		(0.002)	(0.002)		(0.001)	(0.005)		(0.006)
EMEAN_POP	-9.665 ***		-6.292 ***	-2.714		0.504	-14.785 ***		-15.546 ***
	(2.696)		(2.449)	(1.746)		(1.197)	(3.704)		(4.394)
ROUGH_POP	5.508 *		6.943 ***	-0.190		1.946	9.905 **		9.629 ***
	(3.047)		(2.201)	(5.146)		(3.280)	(4.519)		(3.590)
ESD_POP	25.672 ***		21.340 ***	1.005		-0.258	-4.665		31.389
	(5.538)		(5.185)	(4.611)		(3.095)	(30.867)		(39.083)
LANDLOCKED	-3.625		-4.415 **	-0.835		-1.297	-11.987 ***		-12.151 ***
	(2.373)		(2.016)	(1.747)		(1.011)	(2.400)		(3.322)
TEMPAV_POP	-0.347 ***		-0.073	-0.393 ***		-0.154 ***	-1.128 **		-0.904 *
	(0.101)		(0.074)	(0.081)		(0.057)	(0.504)		(0.504)
TEMPSD_POP	1.141 ***		1.010 ***	-0.338		0.013	1.607 *		1.150
	(0.283)		(0.231)	(0.310)		(0.193)	(0.916)		(0.927)
PRECAV_POP	0.052 ***		0.031 **	-0.005		-0.001	0.056		0.028
	(0.018)		(0.014)	(0.015)		(0.011)	(0.034)		(0.031)
PRECSD_POP	-0.096 ***		-0.025	-0.040 **		0.012	-0.065 *		-0.033
	(0.022)		(0.019)	(0.019)		(0.013)	(0.033)		(0.031)
LGDP		8.105 ***	5.896 ***		5.645 ***	5.313 ***		6.573	2.899 *
		(0.431)	(0.575)		(0.325)	(0.476)		(1.708)	(1.459)
R-squared	0.651	0.639	0.800	0.482	0.764	0.802	0.847	0.297	0.875
Adjusted R-squared	0.629	0.637	0.786	0.437	0.762	0.783	0.800	0.278	0.830

Note: Standard errors in parenthesis. ***, **, * denote being significant at 1, 5, and 10% respectively.

Table 2 Regression results of models 4-6 for non-African and African samples

	Non-African sample (no. of obs. = 113)			African sample (no. of obs. = 39)	
	Model 4NA	Model 5NA	Model 6NA	Model 5A	Model 6A
CONSTANT	15.820	11.410	9.371	11.317	35.876
	(30.558)	(8.386)	(6.891)	(27.934)	(24.803)
DNEW_POP	0.012	0.024 ***	0.008	-0.002	0.004
	(0.014)	(0.008)	(0.006)	(0.009)	(0.041)
EMEAN_POP	4.446	-0.113	6.004	14.238	23.633
	(11.484)	(5.901)	(6.049)	(8.892)	(16.093)
ROUGH_POP	-42.395	-11.159	-28.920	-11.363	-47.695 **
	(46.044)	(16.268)	(20.861)	(7.674)	(22.006)
ESD_POP	14.287	-17.970	-1.130	-23.372	-141.991
	(30.076)	(14.085)	(22.338)	(43.861)	(121.637)
LANDLOCKED	-10.655	-2.136	-2.741	14.234	53.000 **
	(8.015)	(3.178)	(3.412)	(10.186)	(21.007)
TEMPAV_POP	0.222	0.647 ***	0.351*	0.640	-1.017
	(0.816)	(0.226)	(0.186)	(0.806)	(0.985)
TEMPSD_POP	2.752	0.478	1.102	-1.519	-7.236 **
	(2.484)	(0.697)	(0.808)	(1.505)	(3.597)
PRECAV_POP	0.013	0.024	0.008	-0.029	0.011
	(0.118)	(0.055)	(0.030)	(0.031)	(0.168)
PRECSD_POP	-0.160	-0.181 *	-0.098	0.042	-0.212
	(0.143)	(0.099)	(0.075)	(0.042)	(0.460)
LGDP	6.445 **	6.888 ***	7.063 ***	7.339	0.885
	(3.197)	(1.053)	(0.830)	(5.595)	(4.508)
DNEW_POP*LGDP	-0.002				
	(0.002)				
EMEAN_POP*LGDP	-0.483				
	(1.329)				
ROUGH_POP*LGDP	4.909				
	(5.145)				
ESD_POP*LGDP	-1.420				
	(3.427)				
LANDLOCKED*LGDP	1.151				
	(0.853)				
TEMPAV_POP*LGDP	-0.040				
	(0.085)				
TEMPSD_POP*LGDP	-0.304				
	(0.265)				
PRECAV_POP*LGDP	-0.001				
	(0.013)				
PRECSD_POP*LGDP	0.021				
	(0.017)				
CLIMATE*LGDP		-0.130 ***		-0.235 ***	
		(0.003)		(0.071)	
CLIMATE*LGDP_FITTED			-0.123 ***		-0.156 ***
			(0.005)		(0.010)
CLIMATE*LGDP_RESIDUE			-0.275 ***		-0.054
			(0.101)		(0.037)
R-squared	0.845	0.812	0.826	0.899	0.906
Adjusted R-squared	0.813	0.791	0.805	0.858	0.862

Note: Standard errors in parenthesis. ***, **, * denote being significant at 1, 5, and 10% respectively.

Table 3 Countries of Four Categories of Climatic Conditions

Good for health, good for production	Bad for health, good for production	Good for health, bad for production	Bad for health, bad for production
Algeria (LM)[1]	Antigua and Barbuda (H)	Afghanistan (L)	Bhutan (LM)
Bahrain (H)	Barbados (H)	Armenia (LM)	Bolivia (LM)
Bulgaria (UM)	Cuba (LM)	China (LM)	Burundi (L)
Croatia (UM)	Czech Republic (H)	Georgia (LM)	Central African Republic (L)
Estonia (H)	Gambia (L)	Iran (LM)	Chad (L)
Finland (H)	Iceland (H)	Kazakhstan (UM)	Chile (UM)
Germany (H)	Ireland (H)	Kyrgyzstan (L)	Comoros (L)
Greece (H)	Luxembourg (H)	Micronesia (LM)	Costa Rica (UM)
Italy (H)	Saint Kitts and Nevis	Mongolia (L)	Ecuador (LM)
Kuwait (H)	Senegal (L)	Pakistan (L)	Ethiopia (L)
Latvia (UM)	Somalia (L)	Russia (UM)	Guatemala (LM)
Lithuania (UM)	Swaziland (LM)	Sudan (L)	Myanmar (L)
Oman (UM)	Switzerland (H)	Tajikistan (L)	Nepal (L)
Poland (UM)		Turkmenistan (LM)	Niger (L)
Qatar (H)		Uzbekistan (L)	Rwanda (L)
South Korea (H)			Uganda (L)
Moldova (LM)			Zambia (L)
Tunisia (LM)			
Ukraine (LM)			
United Arab Emirates (H)			

(1). World Bank income level classification: L = low; LM = lower-middle; UM = upper-middle; H = high.

Appendix: Data Sources

The mortality data are sourced from the year 2000 national life tables published by the World Health Organization (WHO). The WHO life tables provide information on the mortality rates of 22 age groups for both sexes. There are totally 191 country life tables. We exclude countries that are in war at or immediately prior to year 2000. The availability of the other data further restricts our samples to 152 or less, depending on the specifications. Data for climate are sourced from Geographically based Economic Data (GEcon 1.3) project developed by William Nordhaus at Yale University and colleagues. Data and detail documents are available at http://gecon.yale.edu/. We retain the same variable notations as in GEcon 1.3; however, we adjusted the variables by population distribution within each country using the population data (POP90) in the dataset. Data for income per capita (PPP, constant 2000 international dollar) are sourced from the World Development Indicators (WDI) database. Data for HIV prevalence data are sourced from the WHO Statistical Information System (WHOSIS). Tables A1 and A2 provide the summary statistics and correlation coefficients of the non-dummy variables.

Table A1 Summary statistics of non-dummy variables

Full sample (152 obs.)	LE	LGDP	DNEW_POP	EMEAN_POP	ESD_POP	ROUGH_POP	TEMPAV_POP	TEMPSD_POP	PRECAV_POP	PRECSD_POP
Mean	66.17	8.48	254.33	0.48	0.08	0.23	18.42	4.42	97.38	54.27
Median	69.20	8.53	112.71	0.31	0.03	0.17	20.89	3.80	81.77	39.79
Maximum	81.30	10.55	1986.44	2.31	0.77	1.43	28.72	14.12	379.33	195.24
Minimum	36.60	6.21	4.34	0.00	0.00	0.00	-1.25	0.20	3.88	4.24
Std. Dev.	10.77	1.06	364.60	0.46	0.14	0.22	7.75	3.27	63.94	40.90
Non-African sample (113 obs.)										
Mean	70.79	8.79	238.16	0.46	0.10	0.23	16.69	5.07	98.12	47.15
Median	70.70	8.70	85.46	0.30	0.03	0.19	16.37	5.52	80.42	31.93
Maximum	81.30	10.55	1986.44	2.31	0.77	0.69	27.29	14.12	379.33	178.26
Minimum	53.00	6.61	4.34	0.00	0.00	0.00	-1.25	0.20	6.70	7.43
Std. Dev.	6.09	0.94	389.27	0.47	0.16	0.18	8.01	3.45	66.51	38.31
African sample (39 obs.)										
Mean	52.79	7.56	301.17	0.52	0.03	0.21	23.44	2.54	95.23	74.89
Median	51.60	7.48	180.57	0.38	0.01	0.10	23.96	2.03	86.85	77.37
Maximum	71.30	9.55	1037.12	1.97	0.13	1.43	28.72	6.67	208.82	195.24
Minimum	36.60	6.21	18.89	0.03	0.00	0.01	12.74	0.68	3.88	4.24
Std. Dev.	10.22	0.85	280.36	0.43	0.03	0.30	3.85	1.59	56.60	41.63

Table A2 Correlation coefficient of non-dummy variables

Full sample (152 obs.)	LE	LGDP	DNEW_POP	EMEAN_POP	ESD_POP	ROUGH_POP	TEMPAV_POP	TEMPSD_POP	PRECAV_POP	PRECSD_POP
LE	1									
LGDP	0.80	1								
DNEW_POP	-0.34	-0.33	1							
EMEAN_POP	-0.26	-0.29	0.39	1						
ESD_POP	0.03	-0.16	0.23	0.71	1					
ROUGH_POP	0.09	-0.12	-0.06	0.43	0.50	1				
TEMPAV_POP	-0.45	-0.45	-0.25	-0.21	-0.15	0.05	1			
TEMPSD_POP	0.33	0.30	0.45	0.10	0.02	-0.21	-0.79	1		
PRECAV_POP	-0.04	-0.14	-0.33	-0.19	-0.03	0.28	0.46	-0.67	1	
PRECSD_POP	-0.41	-0.49	-0.17	-0.05	0.03	0.13	0.61	-0.64	0.67	1
Non-African sample (113 obs.)										
LE	1.00									
LGDP	0.87	1.00								
DNEW_POP	-0.36	-0.34	1.00							
EMEAN_POP	-0.29	-0.40	0.40	1.00						
ESD_POP	-0.26	-0.37	0.28	0.80	1.00					
ROUGH_POP	-0.26	-0.38	0.05	0.66	0.69	1.00				
TEMPAV_POP	-0.36	-0.31	-0.36	-0.19	-0.05	0.15	1.00			
TEMPSD_POP	0.15	0.14	0.55	0.12	-0.06	-0.27	-0.78	1.00		
PRECAV_POP	-0.20	-0.22	-0.33	-0.19	-0.04	0.27	0.56	-0.74	1.00	
PRECSD_POP	-0.40	-0.46	-0.21	-0.01	0.13	0.26	0.62	-0.62	0.69	1.00
African sample (39 obs.)										
LE	1.00									
LGDP	0.54	1.00								
DNEW_POP	-0.66	-0.37	1.00							

EMEAN_POP	-0.43	0.05	0.33	1.00						
ESD_POP	-0.01	0.03	-0.13	0.64	1.00					
ROUGH_POP	0.45	0.25	-0.32	0.05	0.22	1.00				
TEMPAV_POP	-0.12	-0.42	0.17	-0.71	-0.69	-0.18	1.00			
TEMPSD_POP	0.13	0.30	0.13	0.20	0.15	-0.23	-0.53	1.00		
PRECAV_POP	0.14	0.02	-0.33	-0.18	-0.03	0.34	0.24	-0.73	1.00	
PRECSD_POP	-0.17	-0.28	-0.17	-0.25	-0.21	-0.02	0.43	-0.68	0.77	1.00