The Long-Lived Effects of Historic Climate on the Wealth of Nations

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Abstract

We investigate the long-run consequences of historic climate (1730-2000) for the cross-country income distribution. Using a newly constructed dataset of temperature stretching over three centuries, we estimate a robust and significant time-varying, non-monotonic effect of temperature upon current incomes for a cross-section of 169 countries. We find a large, positive effect of 18th century temperature and an even larger, negative effect of 19th century temperature upon current incomes. When historic temperatures are introduced, the effect of current temperature on current income is insignificant. Our findings suggest that temperature's indirect effect upon income through historical channels dominates any direct contemporaneous effect. We provide evidence on one possible channel by which historic temperature affects current income that focuses on the interaction between agricultural productivity, international trade, and industrialization.

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1 Introduction

The idea that a country's geographic endowment may have long-lived effects upon its economic development has featured in a number of recent contributions. Such effects are argued to operate either directly (e.g., Gallup, Sachs, and Mellinger (1999) and Sachs (2001)), or indirectly, via interactions with historic events (e.g., Sokoloff and Engerman (2000), Acemoglu, Johnson, and Robinson (2001, 2002), Nunn and Puga (2007), and Engerman and Sokoloff (2008)). A key difficulty in empirically evaluating such arguments is the time-invariant character of many components of a country's geographic endowment (e.g., ecology, elevation, latitude, ruggedness, etc.).[1] Albeit slow-moving, the time-varying character of climate offers the possibility to disentangle its historic effects on current economic outcomes from its contemporaneous effect. The growing availability of paleoclimatic estimates of temperature has made such empirical investigations feasible.

In this paper, we examine the effects of climatic variations over the past three centuries on current income per capita in a large sample of 169 countries. Combining a variety of data sources, we construct a new dataset on historic temperature at the country-level. Our primary source of historic temperatures is the Mann, Bradley, and Hughes (1998a, 2004) reconstructed temperature data spanning 1730-1980. We map the spatially gridded temperature data to countries to create a set of country-level, area-weighted, 80-year mean temperatures for the 18th, 19th, and early 20th centuries. As our primary interest is in the effects of climatic variation, we focus upon long, time averages of temperature.[2] Using the newly constructed data, we are able to document the effects of current (late 20th century) and historic (18th, 19th, and early 20th century) temperatures on the current cross-country distribution of real income per capita.

Our findings are both surprising and intriguing. The negative relationship between

[1] Nunn and Puga (2007) employ an interesting identification strategy to estimate time-varying effects of a time-invariant geographic characteristic (ruggedness). Namely, they interact the geographic characteristic with a time-varying, historic variable (slave exports). In this manner, one can disentangle the indirect effect of a geographic characteristic that operates through its interaction with historic events from its direct effect.

[2] See the World Meteorological Organization (2008) for a discussion of the definition of climate. Throughout the paper, we use the terms climatic temperature and temperature interchangeably.

current temperature and income across countries that is commonly estimated (e.g., Nordhaus (2006) and Dell, Jones, and Olken (2009)), appears to reflect the long-run effect of temperature variations in the 18th and 19th centuries, rather than the effect of current temperature alone. Moreover, temperature has a time-varying, non-monotonic effect upon income. Specifically, we find that 18th century temperature has a positive and large effect upon current incomes, while 19th century temperature has a negative and even larger effect upon current incomes. By contrast, once the influence of historic climate has been accounted for, 20th century temperature has a small, positive but insignificant effect upon current income. These results are robust to a host of sub-sample stability and specification checks. They imply that temperature has had a powerful indirect influence through its historical effects on economic development. This dominates any direct contemporaneous effect.[3]

Quantitatively, historic temperatures have substantial, additional explanatory power for current income. When added to a simple regression of current income upon current temperature, explanatory power rises by nearly three-quarters (R^2 rises from 0.16 to 0.27). Moreover, the overall marginal effects of temperature shifts on current per capita income are different across the benchmark and augmented specifications. As a concrete example, consider the case of Sudan and Canada. These two countries have current (2000) real incomes per capita that differ by a factor of 26. If Sudan had experienced Canada's temperature profile instead of its own over the last three centuries, then our results suggest that its income per capita in the year 2000 would have been 27 times larger, essentially accounting fully for the current observed income difference. On the other hand, a similar thought experiment using only the 20th century temperature difference between Sudan and Canada would predict that Sudan's income would be only 8 times larger.

How do we interpret the change in historic temperature's effect upon current income? Drawing upon insights from Krugman (1987) and Matsuyama (1992), we provide an ex-

[3] Using an instrumental variables approach, Easterly and Levine (2003) and Rodrik, Subramanian, and Trebbi (2004) demonstrate that aspects of geography (latitude, settler mortality, mineral endowments, etc.) have no direct effect on income, but have strong indirect effects through institutions. However, see Sachs (2003) for a vigorous counterargument.

planation that focuses on the interaction between agricultural productivity, international trade, and industrialization. Consider a small, open economy with two sectors (agriculture and manufacturing) in the early industrial era (18th century). Suppose that it experiences a climatic temperature rise (warming) which negatively affects domestic agricultural productivity. The temperature rise implies that the country acquires a comparative advantage in manufacturing, leading to an acceleration in industrialization relative to a country with a comparative advantage in agriculture. This in turn has beneficial implications for the country's long-run economic performance and is consistent with the *positive* effect of 18th century temperature we find. Moreover, the presence of feedback effects (e.g., learning-by-doing as in Krugman (1987) and human capital deepening as in Galor and Mountford (2006, 2008)) solidifies the pattern of comparative advantage. This implies that a climatic temperature rise in the 19th century does *not* reverse the comparative advantage established in the previous century. Instead, a negative agricultural productivity shock has a pure negative effect, consistent with the negative temperature effect that we find. We construct measures of historic openness to investigate this explanation. We find that historically *more* open countries experience a *larger* positive effect of 18th century temperature upon current income.

The paper proceeds as follows. In section 2, we describe the historic temperature data. We also discuss the population data that enter into the historic openness analysis. In section 3, we present our empirical model and associated findings. We begin with our baseline results and their interpretation. We then discuss the set of sub-sample stability and specification (additional geographic controls) checks that we undertake. In section 4, we discuss and evaluate our proposed explanation of climate's time-varying effects, focusing upon the interaction between agricultural productivity, comparative advantage, and development. Finally, in section 5, we summarize our findings and their implications for future research.

2 Historic Data Description

As noted in the introduction, we bring together a variety of data sources to construct the country-level current and historic temperature measures. First, we describe the temperature and boundary datasets and how they enter into the construction of country-level, mean temperatures. Second, we review the nature of the reconstructed temperature data and the evidence for their reliability. Third, we discuss the rough patterns visible in the current and historic temperature series. Fourth, we describe the historic demographic data which is used to construct additional explanatory variables.

2.1 Temperature Data

The temperature datasets that we use are:

- the CRUTEM3 global surface temperature dataset from the University of East Anglia's Climatic Research Unit. The temperature data (in degrees Celsius/C) are at a monthly frequency at a 5 degree grid spatial resolution, from 1850–present. The coverage in the earlier years is somewhat sparse, reflecting the availability of the underlying instrumental data (wide coverage is available only post-1900). See Brohan, Kennedy, Harris, Tett, and Jones (2006), Jones, New, Parker, Martin, and Rigor (1999), and the Climatic Research Unit website for complete details.

- the Mann, Bradley, and Hughes (1998a, 2004) reconstructed global surface temperature anomalies (hereafter, MBH). The temperature data (in degrees C) are at an annual frequency at a 5 degree grid spatial resolution, from 1730–1980. The spatial coverage (dimensions) does not vary over the period. See these papers and the associated data documentation for complete details.

The first step in using the temperature data is to convert the anomalies (differences in temperature relative to some baseline) to absolute temperature measures. We use the CRUTEM3 data to construct the 1902-1980 mean temperature which forms the baseline for the MBH data. These mean temperatures are then added to the anomalies data to recover the absolute temperatures at the gridpoints from 1730-1980.

Following the World Meteorological Organization (WMO), we define the climatic temperature as the mean, annual temperature for a location over *at least* a thirty-year period (World Meteorological Organization, 2008). As a measure of recent temperature, we take the thirty-year mean of temperature at each gridpoint over the period 1970-1999 (the climatic period roughly contemporaneous with the economic data and previous empirical investigations). Since the MBH data do not span the full 20th century, we use the CRUTEM3 data to construct the late 20th century climatic temperature.

For our measures of historic temperatures, we take the multi-year means of the MBH temperature data at each gridpoint within sub-periods prior to 1970 (back to 1730). Specifically, we divide the period 1730-1969 into 3 historic windows of 80 years each: 1730-1809, 1810-1889, and 1890-1969. Our first two windows exhibit a rough correspondence to the dates cited for the First and Second Industrial Revolutions (Mokyr, 2000). In such a way, we attain two objectives: (a) we exhaust the historic temperature data available to us, thereby achieving a greater degree of precision for any calculated mean temperatures; and (b) multiple, contiguous climate windows allow for time-varying, historic effects of temperature to manifest. In the choice of windows, we have tried to balance the ability of the empirics to disentangle the temperature effects associated with each period (by decreasing the number of windows) and the need to ensure that important historical patterns are identified (by increasing the number of windows).[4] For brevity, we will refer to each temperature variable by its predominant, underlying historic era (e.g., 18th century, 19th century, and early 20th century).

In a second step, we spatially join the gridpoint mean temperature data to the administrative boundaries data from the U.S. Geological Survey's Global GIS database

[4] We have also estimated our models with either a greater or lesser number of historic temperature variables. Patterns of temperature effects seen in our baseline specification are generally maintained in specifications with a greater number of windows, but with higher standard errors (reflecting that mean temperature is slow-moving). Specifications with a lesser number of windows generally lead to a smearing of historic temperature's effects (reflecting the implicit averaging of effects from finer windows).

(2003). The administrative boundaries data allow us to link the temperature data to the country-level economic data, via common country identifiers.

Finally, we use the merged temperature and map data to calculate area-weighted, mean temperature for each time period and country. The area weights are time-invariant, allowing us to be certain that any variation in mean temperature's effect across time is purely a function of temperature variation (rather than time-varying weights).[5]

One of the limitations of the temperature data is that the spatial resolution is comparatively low – a 5 degree (latitude/longitude) grid size corresponds to an approximately 550 kilometer grid size at the equator. Since we match the data to countries, the spatial resolution is not as binding as it would be if we were to consider direct gridpoint effects.[6] If anything, the coarseness of the temperature data reduces the variability of the country-level aggregated temperature measures, inhibiting our ability to separately identify current and historic temperature effects.

2.1.1 Reliability of the Temperature Data

Due to the paucity of high resolution, direct (instrumental) temperature data prior to the 20th century, researchers have deployed statistical methods to reconstruct historic temperature series from both direct and indirect, or proxy, measures. In their temperature reconstruction, MBH draw upon a wide spatial network of annual temperature indicators, including instrumental records, tree rings, ice cores, ice melts, coral bands, and other geological evidence. The temperature signal from these myriad data series is

[5] We have also conducted the analysis with time-varying, historic population weights used to calculate historic, mean temperatures (see section 2.2 for a description of the underlying population data and weights calculation). A concern with such weights is that they may lead to an *over*weighting of urban relative to rural temperatures, which in turn is related to the production mix of an economy (less versus more agricultural). The results lead to roughly similar patterns in terms of temperature's effects, although the estimated magnitudes of the effects are usually smaller. Signs and statistical significance are typically unchanged.

[6] See Nordhaus (2006) for an application that takes the opposite approach. He disaggregates the macroeconomic data and matches it to geographic gridpoints. In our approach, we are allowing a country's borders and spatial extent to be endogenous to historic temperature. A country's borders and spatial extent are therefore channels by which historic temperature may influence current performance. See Burke, Miguel, Satyanath, Dykema, and Lobell (2009) for an example of how borders may be indirectly affected by temperature. They find that warming increases the risk of civil war in Africa (which in turn may affect borders).

then recovered by calibrating the relationship between the climatic indicators and the instrumental record where they overlap. The estimated relationship may then be used to "predict" temperature in earlier periods as a function of the temperature proxies (see Committee on Surface Temperature Reconstructions for the Last 2,000 Years (2006) for a discussion of the general approach).

How reliable is the temperature signal in the dataset? Since its initial publication in 1998 and subsequent posting of corrections (Mann, Bradley, and Hughes, 2004), the MBH data have been the subject of a host of cross-validation studies (e.g., Jones, Osborn, and Briffa (2001), Bradley, Briffa, Cole, Hughes, and Osborn (2003), Mann, Rutherford, Wahl, and Ammann (2005, 2007), Li, Nychka, and Ammann (2007)). A study by Wahl and Ammann (2007) undertook a variety of different statistical corrections to the underlying MBH methodology and found that the patterns amongst the reconstructions remained robust. Despite such reassurances, a core concern remains that temperature reconstructions tend to *under*state the degree of variability of past climate (von Storch, Zorita, and González-Rouco, 2009). As we noted earlier with respect to spatial resolution, any reduced variability in the temperature series will inhibit our ability to disentangle current and historic temperature effects.

2.1.2 Patterns in Historic Temperatures

Table 1 presents some summary statistics of the temperature and other key variables. Our full sample consists of 169 countries for which both temperature and current income exist. The two types of variation in the temperature data that we exploit in this paper can be gleaned from this table: the cross-century and the cross-country variation in climate. With regards to the former, what we see in table 1 is a slight decrease in average temperature of 0.085 degrees C, going from the 18th to the 19th century, followed by a rise of 0.114 degrees C, going from the 19th to the early 20th century. The largest change occurs within the 20th century, as the global mean temperature rises by 0.292 degrees C from the early to the late 20th century. Interestingly, despite the aggregation of the temperature data to the country-level, these patterns replicate the features seen time and again in various historic global temperature series (Jones and Mann, 2004). There is clearly a large persistent element in climatic temperatures, which is not surprising. As shown later, the cross-century variation is still sufficient to separately identify the effects of current and historic temperatures. The cross-country variation within any century is substantial, with the hottest countries having mean temperatures in the high 20s degrees C and the coldest countries having mean temperatures that slightly below 0 degrees C.

2.2 Demographic Data

Historic population data come from the Historical Database of the Global Environment (HYDE, version 3.1), constructed by the Netherlands's Environmental Assessment Agency (denoted MNP). The database contains information on the spatial distribution of global population at a decadal frequency from 1700–2000. Similar to the temperature reconstructions, a variety of historical and proxy data are used to construct measures of past population distribution. These are then carefully linked to modern population databases to verify their efficacy and ensure continuity (e.g., Tobler, Deichmann, Gottsegen, and Maloy (1995)). Cross-validation with respect to other historical population databases was then undertaken, including Mitchell (2007) and Maddison (1995).[7] We use the HYDE population data to construct:

1. country urbanization rates in 1730 (used in the sub-sample analysis)
2. country population centroids in 2000 (used in the geographic controls)
3. country population size in 1730
4. country openness in 1730

The HYDE classification of population into urban and rural is used to calculate a country's urbanization rate in 1730 (the initial year for which we have temperature data).

[7] See Klein Goldewijk (2005) and the associated data documentation for complete details on the population data construction.

Country population centroids are calculated according to the method in U.S. Census Bureau (2001). Each centroid is equivalent to a country's center-of-mass, where the country's component areas are weighted according to the size of the resident population. We describe the calculation of historic country population and openness in section 4, where these measures are used.

Further details regarding the underlying data sources are available in table A.1 in the appendix. Summary statistics for the key variables that we use are presented in table 1.

3 Empirical Results

In this section, we detail the econometric methods employed and our baseline results on the relationship between current income and current and historic temperatures. We then present a set of robustness checks of our findings, including estimation over various sub-samples and the addition of other geographic controls. We conclude with some discussion and interpretation of our results.

3.1 Baseline Results

Since our primary focus is the explanation of cross-country patterns of material well-being, the core macroeconomic variable that we investigate is real income per capita. We use the natural logarithm of the Penn World Table (Heston, Summers, and Aten, 2006) measure of real GDP per capita (1996 constant international dollars) in the year 2000 as our dependent variable.[8]

In our core empirical analysis, we estimate the effect of temperature (current and historic) upon income in a linear regression with the general form:

$$\begin{aligned} y_i \;=\;& \alpha + \beta_1 temp_{1970-1999,i} + \beta_2 temp_{1890-1969,i} + \beta_3 temp_{1810-1889,i} \\ & + \beta_4 temp_{1730-1809,i} + \sum_{k=1}^{K} \gamma_k x_{k,i} + \varepsilon_i, \qquad (1) \end{aligned}$$

[8]As robustness checks, we also considered real GDP per worker in 2000 and average real GDP per capita over 1980-2000, similarly extracted from the Penn World Table. The results are broadly unchanged.

where i indexes countries, y denotes the dependent variable (log real income per capita), $temp$ denotes mean temperature for country i during the time period in the subscript, x is a set of K additional explanatory variables, ε is a mean-zero error term, and the remaining Greek letters denote parameters. In our baseline specification, we only include the temperature variables as explanatory variables ($\gamma_k = 0 \; \forall \; k$), estimating a reduced-form effect of climatic temperature on the dependent variable.[9] We also undertake a host of robustness checks, including sub-sample regressions and the inclusion of various geographic controls.

In all of our specifications, we do not include explanatory variables that are correlated with economic performance and known to be endogenous (e.g., institutions, human capital, physical capital etc.). Since these variables are endogenous to the development process, they lie along the causal path from current and historic temperatures to real income. Consequently, their inclusion would bias the coefficients on the exogenous climate variables – they would no longer represent the reduced form effect of climate, nor even the reduced form effect of climate conditional on the other controls.[10]

Coefficients are estimated by ordinary least squares. Standard errors are Huber-Eicker-White heteroskedasticity-robust. We also calculated spatially-corrected standard errors (unreported), finding that they make little difference to our conclusions.[11]

In panel 1 of table 2 we report the coefficient estimates of (1), where we only include current temperature (1970-1999) as an explanatory variable. This specification is a natural benchmark against which to judge the effects of historic climate. For our full sample of 169 countries (column 1), we find that a one degree C rise in current temperature is

[9] It would be interesting to undertake a broader investigation of the role of a country's historic climate by including historic, climatic measures of precipitation, wind, humidity, etc. into the analysis. Unfortunately, such historic or reconstructed series do not currently exist with a sufficiently global coverage to make such an extension feasible.

[10] We provide an explicit derivation of the bias in an unpublished appendix (available upon request). In a similar vein, Angrist and Pischke (2008) discuss how the inclusion of outcome variables as controls leads to selection bias affecting any estimated treatment effects. See section 3.2.3 of their text.

[11] In particular, we calculated standard errors assuming either a spatial AR(1) process to the errors or a general form of cross-section, spatial dependence, using the method described by Conley (1999). The differences between the two sets and the more usual White standard errors were not marked. Results are available upon request.

associated with a 5.9% reduction in real GDP per capita. This estimate is largely in line with those reported in previous studies that have used other current temperature data to study the cross-sectional temperature-income relationship (e.g., Dell, Jones, and Olken (2009)). The negative relationship between income and current temperature can also be seen in the top panel of figure 1 where we fit both a linear, parametric and a non-linear, nonparametric regression curve to the datapoints (see section 3.1.1 for details on the nonparametric methods used). No strong nonlinearities in the simple relationship between income and current temperature are evident.[12] We discuss the larger set of nonparametric results in more detail below.

In panel 2 of table 2, we add mean temperature in the early 20th (1890-1969), 19th (1810-1889), and 18th (1730-1809) centuries as explanatory variables. Several aspects of the full sample estimates in column 1 are worth highlighting. First, the R^2 of the regression rises from 0.16 to 0.27, suggesting that historic temperatures have substantial explanatory power for current income over and above that of current temperature. These four temperature variables can account for over a quarter of the variability in the current income distribution. Second, the coefficients on the earlier historic temperature variables are highly significant and have opposite signs – positive for the 18th century and negative for the 19th century. The coefficient on temperature from the early 20th century is almost zero and insignificant. Third, the magnitude of the 19th century temperature effect is larger than the 18th century effect. Fourth, current (late 20th century) temperature is positively associated with income once we control for the effect of historic temperatures. However, the comparative magnitude of current temperature's effect is small and statistically insignificant. Finally, the sum of the estimated coefficients on current and historic temperatures is -0.043, which is similar in magnitude to the effect we obtain when we regress income on current temperature alone (-0.059). These are not statistically significantly different at conventional levels. This suggests that the latter is capturing a

[12]The lower panel of figure 1 shows the simple relationship between income and current temperature fitted to the sample with outliers excluded (described below). As can be seen, the match between the linear, parametric and nonparametric fits is even higher.

long-run effect of temperature on income, which our baseline specification decomposes into current and historic components. Thus, we are able to ascertain that the negative relationship between current temperature and current income is *not* due to current temperature's effect on income (which is estimated to be small and positive but insignificant), but rather arises from the large, negative effect of 19th century temperature.

To determine whether outliers are driving the results, we re-estimated our baseline specification excluding 9 countries that Cook's distance criterion assesses as being influential observations.[13] The estimation results are in column 2 of table 2. We find a similar pattern of coefficient signs and relative magnitudes as in the full sample results. The statistical significance of the two earlier historic temperature coefficients is unchanged, while the coefficient on current temperature is larger but still insignificant. The sample of 160 countries with statistical outliers excluded is our baseline sample; all subsequent analysis is founded upon the baseline sample unless otherwise indicated. A visual guide to the nature of the identifying variation leveraged in the core regression for the baseline sample is given by figure 2. The partial association plots demonstrate how the intercentennial variation in climatic temperatures is sufficient to separately identify the current and historic effects.

3.1.1 Non-linearities in Temperature's Effects

To account for possible nonlinearities in the effects of temperature upon income, we also fitted two nonparametric regressions for real income. The first included only current temperature as the explanatory variable, while the second augmented the set of explanatory variables with the 3 historic temperature variables used in our baseline specification. In both cases, the curve-fitting was done by thin-plate regression splines, under the assumption that the model is generally additive (Wood, 2003, 2006). Thus, each explanatory variable separately affects the outcome variable according to an unknown and arbitrary

[13]We drop observations for which the Cook's distance statistic is greater than $\frac{4}{N}$, where N is the number of observations (Andersen, 2008). The statistical outliers flagged are: Afghanistan, Australia, Bhutan, Cyprus, the Democratic Republic of Congo, Mongolia, North Korea, Singapore, and Tajikistan.

functional form (which is fitted by the thin-plate spline procedure). The nonparametric results when current temperature is the only explanatory variable are seen in the top panel of figure 1 (described earlier).[14]

For the second nonparametric regression, the model allows for each of the 4 temperature variables (current and historic) to affect income via unknown, smooth functions. Figure 3 shows the nonparametric equivalent of the partial associations of the temperature variables with income, where the effect of each temperature variable upon income changes with the level of the temperature variable. Similar to the univariate case (with current temperature alone), there is little evidence of any substantial non-linearities in these relationships within the baseline sample.[15] Moreover, the nonparametric results broadly replicate the pattern of signs, relative magnitudes, and statistical significance of the estimated linear regression coefficients in the baseline specification. These results support the relevance of the estimated effects from the linear models that form the core of our analysis.

3.1.2 Temperature Effect Magnitudes

The effects of historic temperature are not only statistically significant, but also economically significant. As an illustrative example, consider a country at the median of the global temperature distribution in each century. If that country were to move to the 90th percentile of the global temperature distribution in each century, its current income per capita income would be predicted to fall by 36% using the estimates from regression 2 in table 2. If the effects of historic temperature are omitted (panel 1 in table 2), the marginal effect of such a move is reduced to -27%. The income effect of such a shift within the temperature distribution is 30% larger when the historic elements of temperature are introduced. Moreover, the difference in effects is significant at a 12.5% level.

[14]The upper bound on the basis dimension for the individual smoothing terms in the generalized additive models is set to 15. Additional details and the associated R program files are available upon request.

[15]We also experimented with large increases in the effective basis dimension of the underlying penalized spline-fitting procedure (which *reduces* the amount of smoothing), but it made little difference to the results.

This highlights the quantitative importance of controlling for historic temperatures.

Taken in isolation, each of the temperature coefficients in our baseline specification is extremely large relative to what is usually estimated if only current temperature is included. The literal interpretation of each of these coefficients is that they represent the unit change effect when all else is held constant. However, in the case of something that is highly persistent, like climatic temperature, the implicit extrapolation undertaken when interpreting each regression coefficient in isolation seems dubious. Nowhere in the sample does a country experience a large temperature change in one century, while its temperature in other centuries are identical.

However, if we use shifts in temperature that are representative of the cross-century variation in temperatures *within* country, the sizes of historic temperature's effects moderate. The average absolute deviation of within-country, cross-century temperature variation is 0.059 degrees C. Such a representative temperature rise in the 18th century would imply a 16% rise in year 2000 income. Moreover, such a representative temperature rise in the 19th century would imply a 23% fall in year 2000 income. Although much more modest in size, these effects are still large. They indicate that small, historic temperature variations have important and long-lasting effects.

3.2 Robustness Checks

In this subsection, we report the outcomes of two types of robustness checks: (i) sub-sample stability (restriction of the estimation sample by various criteria); and, (ii) the addition of a set of geographic controls.

3.2.1 Sub-sample Stability

A common concern in the empirical development literature is that the results may be driven by the inclusion of countries in Sub-Saharan Africa, which typically have suffered from poor economic performance. To address this concern, we re-estimated our baseline regressions excluding these countries. The results are given in the third column of table 2. The absolute magnitudes of the temperature coefficients and the R^2s fall, but the same pattern of signs, relative magnitudes, statistical significance, and marginal explanatory power of the historic temperature variables is similar to that seen in the baseline sample.

We also check whether the results are robust to a host of other sub-samples, which exclude various sets of countries that have been highlighted in the literature. This includes sub-samples that exclude: OPEC member countries, the Former Soviet countries, current high income countries, current low income countries, countries with high urbanization rates in 1730, and countries with low urbanization rates in 1730. The current high/low income indicator is determined by whether or not a country is above or below median real income per capita in 2000.

Although a high/low income split is often presented in sub-sample stability analysis, such an exercise implicitly uses an outcome variable (current income) as an explanatory variable in creating the split. This means that it is subject to the biases described in section 3.1. Accordingly, we prefer the use of the *initial* development level in defining the relevant high/low development level sub-samples (which is presumably the purpose of undertaking the high/low current income split). Following earlier work (DeLong and Shleifer, 1993; Ades and Glaeser, 1999; Acemoglu, Johnson, and Robinson, 2002), we use the urbanization rate in 1730 as a proxy for initial development level. The high/low urbanization rate in 1730 indicator is determined by whether or not a country is above or below the median 1730 urbanization rate (see section 2.2 for a discussion of the historic population data).

These results are reported in the fourth through ninth columns of table 2. While the magnitudes of the effects of temperature on income vary across these sub-samples, the general pattern in terms of signs and relative magnitudes is remarkably robust. In spite of possible biases, it is even evident in the sample which excludes current low income countries – these effects manifest amongst the current high income countries. Moreover, temperature effects in the sub-sample excluding the more developed countries in 1730 are larger in magnitude than those from the sub-sample excluding the less developed countries in 1730. Thus, countries that are further along the modern development path are *less* affected by temperature variations than are less-developed countries. We do see two sub-samples where 18th century temperature, albeit positively related to current incomes, is statistically insignificant – the sub-samples where former Soviet countries are excluded (p-value of 15%) and where the less developed countries in 1730 are excluded (p-value of 54%).

3.2.2 Geographic Controls

Table 3 shows the results when a variety of geographic controls are added to our baseline specification which includes current and historic temperatures. The controls selected are unlikely to lie along the causal path from temperatures to income.

The geographic controls that we employ are: the absolute latitude of a country's year 2000 population centroid (calculated according to the method in U.S. Census Bureau (2001)); elevation in meters (calculated as the average elevation within 100 kilometers of a country's population centroid); average annual precipitation in millimeters over 1970-1999 (calculated as the average precipitation within 100 kilometers of a country's population centroid); an indicator for landlocked (extended from the data underlying Gallup, Sachs, and Mellinger (1998, 1999)); an indicator for the Americas (the Caribbean, Latin America, and North America); an indicator for the Sub-Saharan African region; and a full set of geological continent dummies. The regional designations are taken from the World Bank's country geographic classification (2009). We also investigate two specifications where we include exhaustive, non-collinear combinations of the geographic controls simultaneously.

Of these additional geographic controls, latitude, elevation, landlocked status, and the Sub-Saharan Africa indicator are statistically significant when they are added individually to the baseline regression. As seen in column 7, when the geographic controls are included simultaneously, elevation and the Sub-Saharan Africa indicator are statistically significant (at the 10% and 1% levels respectively). When the continent indicators are included (swapping out the Americas and Sub-Saharan indicators) as in column 8, then only elevation and absolute latitude are statistically significant (both at the 10% level). It is also worth noting that these two exhaustive specifications show that current and historic temperature plus the full set of geographic controls are able to account for more than half of the cross-country variation in current, real incomes.

In all of these regressions, the inclusion of the various geographic controls reduces the magnitudes of the temperature coefficients, but it does not affect the pattern of signs and relative magnitudes seen in the baseline specification. Moreover, the statistical significance of the temperature coefficients is generally unchanged. In particular, the effects of the 19th and 18th century temperature variables remain robust.

4 Historic Climate, International Trade, and Industrialization

Our results reveal a robust, significant impact of historic temperature on current incomes, even after controlling for current temperature. Moreover, we see that the effect of historic temperature has a time-varying effect upon current income, with 18th century climate having a positive effect and 19th century climate a negative effect. The question then arises as to *how* exactly historic temperatures influence current incomes? In what follows, we sketch a candidate explanation and offer some suggestive empirical evidence to support it.

4.1 An Economic Interpretation of our Findings

The starting point for our proposed mechanism is a persistent, negative relationship between temperature and aggregate agricultural productivity. There is substantial modern evidence for such a relationship. For example, Tan and Shibasaki (2003) and Lobell and Field (2007) estimate large negative effects of temperature rises upon crop yields in global datasets. In their evaluation of climate change scenarios, Tubiello, Soussana, and Howden (2007) describe evidence that the negative effects of temperature upon crop yields will likely overwhelm any positive effects associated with higher carbon dioxide concentrations. Finally, Dell, Jones, and Olken (2008) find strong and persistent negative temperature effects upon agricultural output growth amongst poor countries in a panel covering the post-WWII period.

But why do temperature shocks to agricultural productivity in the 18th and 19th century have different effects on current income? We argue that to understand the changing role of agricultural productivity in long-run development, one has to focus on the interaction between agricultural productivity, international trade and industrialization.

Consider two small, pre-industrial economies (e.g., representative for much of the world in the 18th century). Both economies are in a Malthusian state with most of the labor force working in agriculture and food consumption at subsistence level. Manufacturing activity is low. It cannot expand because workers have to stay in agriculture to produce food for subsistence. The standard view in much of the literature is that improvements in agricultural productivity are a prerequisite for industrialization (*inter alia* Johnson (1997), and Gollin, Parente, and Rogerson (2002)). However, Matsuyama (1992) shows that the link between agricultural productivity and industrialization can be *negative* in a small, open economy. To see this, suppose that one of the economies in our example experiences a negative shock to agricultural productivity, while the other economy experiences a positive shock. If the economies are open, these shocks affect the pattern of comparative advantage. The economy with less productive agriculture will specialize in manufacturing, while the economy with more productive agriculture will specialize in agriculture – each economy specializes in the sector for which they have the *lower* domestic opportunity cost. Such specialization makes manufacturing expand in one economy and shrink in the other. Thus, the economy with relatively less productive agriculture starts industrializing, while the economy with relatively more productive agriculture shifts production away from manufacturing. Our finding that 18th century temperature has a positive effect on current income is consistent with a "Dutch disease" effect, as highlighted by Krugman (1987) and Matsuyama (1992).

Consider now the effect of 19th century temperature shocks. Suppose now that the two economies experience the opposite shocks: the economy which specialized in manufacturing experiences a positive agricultural productivity shock (a lower temperature), while the economy which specialized in agriculture experiences a negative shock (a higher temperature). These shocks do not reverse the pattern of comparative advantage established in the previous century. Positive feedback effects in the development process reinforce the pattern of specialization established by the earlier distribution of comparative advantage.

What might such feedback mechanisms be? Learning-by-doing is one possibility. If such externalities are strong enough, then they can overwhelm any further extrinsic productivity shocks, locking-in comparative advantages (Krugman, 1987). Another possibility is human capital specialization and deepening (Galor and Mountford, 2006, 2008). Suppose that manufacturing entails relatively greater specialization in skill-intensive production than does agriculture. Then, a shift in comparative advantage favoring manufacturing leads to a rise in the demand for human capital. The subsequent increase in human capital investment reinforces the initial pattern of comparative advantage, widening the productivity gap between countries.

With such feedback effects anchoring initial comparative advantages, additional agricultural productivity (temperature) shocks then have two effects. First, there is a pure income effect: higher agricultural productivity generates higher incomes which increases the demand for manufacturing goods relative to food. This leads to a rise in the demand for skills leading to greater human capital investment. Second, a more productive agricultural sector allows for a further reallocation of labor away from agriculture to manufacturing. Both of these effects increase productivity in manufacturing by raising human capital investment. Such a mechanism can ensure that temperature rises (falls) in later periods have long-run negative (positive) effects upon income. This is consistent with our finding that 19th century temperature has a negative effect on current income.

4.2 Historic Climate and Openness Empirics

As alluded to above, we postulate that our core empirical results indicating a positive relationship between current incomes and 18th century temperatures may be partially explained via an interaction with historic openness. To test this proposition, we constructed two measures of historic openness: (1) the log population of a country in 1730; and (2) a gravity-inspired, population-weighted inverse distance measure. According to the arguments advanced by Alesina and Wacziarg (1998) and Alesina, Spolaore, and Wacziarg (2005), population size should be *negatively* related to a country's openness. For both measures, we use the HYDE data, described in section 2.2. The population-weighted inverse distance measure is defined as:

$$invdist_{i,t} = \sum_{j \neq i} \left(\frac{P_{j,t}}{\sum_k P_{k,t}} \right) (D_{i,j,t})^{-1} ,$$

where i, j, and k denote countries; $P_{j,t}$ is the population of country j at time t; and $D_{i,j,t}$ is the great circle distance between the population centroids of country i and j at time t. We use measures dated $t = 1730$ to capture initial conditions of openness (coincident with the start of the temperature series). The weighted inverse distance measure should be *positively* related to a country's openness.

We then introduce these measures of historic openness and their interactions (products) with 18th century temperatures into our baseline specification. The resulting linear regression has the form:

$$\begin{aligned} y_i \quad = \quad & \alpha + \beta_1 temp_{1970-1999,i} + \beta_2 temp_{1890-1969,i} + \beta_3 temp_{1810-1889,i} \\ & + \beta_4 temp_{1730-1809,i} + \sum_{k=1}^{2} \gamma_k open_{k,i} + \sum_{k=1}^{2} \delta_k open_{k,i} \cdot temp_{1730-1809,i} + \varepsilon_i, \end{aligned} \tag{2}$$

where the notation is identical to equation 1 and $open_k$ represents one of our two measures of openness in 1730.

If the mechanism described in the previous section is operative, then we would predict that countries that were historically *more* open and subject to *negative* agricultural productivity shocks (higher climatic temperatures) in the 18th century should be wealthier today. The results seen in table 4 illustrate exactly this.

We consistently see that *less* open countries (proxied by population size in 1730) benefit from *lower* 18th century temperatures, rather than higher 18th temperatures – the coefficient on the interaction term is negative. This is statistically significant across the baseline, Americas excluded, and Sub-Saharan Africa excluded samples. We also see that countries that were *more* open (proxied by the 1730 weighted inverse distance measure) benefit from *higher* 18th century temperatures – the coefficient on the interaction term is positive. This effect is statistically significant in the Americas excluded sample. When both historic openness measures and their interactions are included, the overall patterns are unchanged. All of these results lend support to the contention that historic openness just prior to the industrial revolution may have transformed a short-run negative agricultural productivity shock into a long-run positive specialization driver, by shifting a country's comparative advantage away from agricultural goods.

Additional evidence for such a mechanism is presented in table 5. There, we use agricultural value-added over GDP (in percentage points) as a measure of the current agricultural sector size, and hence, a country's degree of specialization in agriculture. In line with our story, we see that the size of the agricultural sector is *negatively* related to historic temperature rises in the 18th century and that higher openness in the 18th century magnifies the size of the effect, while preserving its sign. The patterns in the results broadly mirror those seen for income per capita, albeit with the opposite signs.

5 Conclusion

Using a newly constructed dataset of country-level, area-weighted temperatures stretching back 270 years, we estimate a robust and significant time-varying, non-monotonic effect of climatic temperature upon current incomes. In particular, we find a large, positive effect of 18th century temperature and an even larger, negative effect of 19th century temperature upon current incomes. When historic temperatures are controlled for, the effect of current temperature on current income is slightly positive and insignificant. The negative relationship between current temperature and current income that is commonly estimated appears to reflect the long-run effect of climatic variations in the 18th and 19th centuries. The results highlight the long-lived effects of historic temperatures upon a country's economic outcomes. A corollary of these findings is that temperature has primarily affected current income *indirectly* via its impact upon a country's historic development. Our paper therefore contributes to the debate regarding geography's effects alluded to in the introduction.

Moreover, we proposed an explanation for the time-varying effects of temperature which relies upon such a channel. When the pattern of comparative advantage in the pre-industrial era is affected by temperature, a temperature *rise* that *depresses* agricultural productivity leads to greater specialization in manufacturing. Positive feedback effects in manufacturing contribute to an entrenchment of comparative advantage. In the absence of temperature-induced shifts in comparative advantage, temperature rises in later periods lead to reductions in contemporaneous income, which are associated with lower current income. To investigate the relevance of historic comparative advantage, we constructed country-level measures of openness in the 18th century. In line with our story, countries which were historically more open exhibited larger positive effects of 18th century temperature.

Our primary purpose in this paper has been to document the nature of the relationship of historic temperatures to current incomes and to consider the evidence for a simple economic explanation of the findings. Our explanation is not exclusive or exhaustive – interactions with other historic events and channels, such as European colonization and international technological diffusion, are also possible. The investigation of such additional interactions lies beyond the scope of the current paper and is left to future research.

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Table 1: Summary Statistics

Variable	Mean	Standard Deviation	Skewness	Kurtosis	Median	Minimum	Maximum	Number of Countries
Real Income per capita (Int'l $)	9245.9	9478.3	1.333	4.130	5268.6	359.2	48217.3	169
Mean Temp. ($^\circ$C), 1970-1999	18.940	7.980	-0.690	2.155	22.368	-2.100	27.810	169
Mean Temp. ($^\circ$C), 1890-1969	18.648	8.051	-0.697	2.176	22.144	-3.090	27.422	169
Mean Temp. ($^\circ$C), 1810-1889	18.534	8.086	-0.697	2.187	21.728	-3.210	27.401	169
Mean Temp. ($^\circ$C), 1730-1809	18.619	8.059	-0.698	2.194	21.972	-3.394	27.343	169
Urban. Rate 1730	0.039	0.06	5.143	39.44	0.018	0.000	0.622	169
Abs. Latitude ($^\circ$)	26.369	16.624	0.334	1.962	22.896	0.253	64.524	169
Elevation (m)	562.4	629.0	2.005	7.480	320.1	0.0	3500.7	169
Precipitation (mm)	1119.97	785.73	0.892	3.285	904.98	26.95	3927.53	167
Log Population in 1730	20.31	3.913	-0.489	2.915	20.977	10.5	30.1	169
Log Inverse Distance in 1730	-8.765	0.533	0.287	2.645	-8.754	-9.7	-7.429	169

Notes: Real income per capita is from the year 2000. The construction of the area-weighted mean temperatures for the late 20th, early 20th, 19th, and 18th centuries is described in the main text. Temperatures are in degrees Celsius. Absolute latitude is the absolute value of the latitude of a country's population centroid in 2000. Elevation (in meters) is the average elevation within 100 kilometers of a country's 2000 population centroid (or nearest point on land for non-convex countries). Precipitation (in millimeters) is derived from the Wilmott and Matsuura global gridded precipitation series (0.5 degree resolution) over the period 1970-1999. It is the average precipitation within 100 kilometers of a country's 2000 population centroid (or nearest point on land for non-convex countries). Population and inverse distance in 1730 are calculated from the population data in HYDE, version 3.1 (see the main text for full details). Skewness is the 3rd central moment divided by the variance raised to the 1.5 power (a symmetric distribution has a value of 0). Kurtosis is the 4th central moment divided by the square of the variance (a normal distribution has a value of 3).

Table 2: Baseline Regression and Sub-sample Robustness Checks
Dependent variable is Logged Real GDP per capita in 2000

Explanatory Variable / Statistic	1	2	3	4	5	6	7	8	9
	Full Sample	Baseline Sample	Sub-Saharan Africa Excluded	OPEC Members Excluded	Former Soviets Excluded	High Income Excluded	Low Income Excluded	High Urban Rate 1730 Excluded	Low Urban Rate 1730 Excluded
					Panel 1				
Mean Temp., 1970-1999	-0.059**	-0.074**	-0.042**	-0.078**	-0.093**	-0.047**	-0.023**	-0.054**	-0.062**
	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)	(0.011)	(0.009)
R^2	0.16	0.261	0.139	0.306	0.329	0.176	0.103	0.149	0.329
					Panel 2				
Mean Temp., 1970-1999	0.204	0.48	0.459	0.548	0.539	-0.033	0.198	0.171	0.556
	(0.370)	(0.342)	(0.374)	(0.336)	(0.376)	(0.334)	(0.259)	(0.497)	(0.354)
Mean Temp., 1890-1969	0.004	1.262	1.014	0.615	1.058	1.441	1.324*	2.288	0.679
	(1.112)	(0.896)	(0.818)	(0.871)	(1.078)	(1.166)	(0.557)	(1.744)	(0.853)
Mean Temp., 1810-1889	-3.639**	-4.307**	-3.585**	-4.13**	-3.64**	-2.641**	-2.639**	-4.046**	-2.107*
	(0.866)	(0.627)	(0.540)	(0.626)	(0.869)	(0.878)	(0.493)	(1.501)	(0.885)
Mean Temp., 1730-1809	3.388**	2.516**	2.085**	2.913**	1.980	1.186†	1.11*	1.533†	0.828
	(0.671)	(0.520)	(0.514)	(0.505)	(1.354)	(0.334)	(0.552)	(0.812)	(1.353)
R^2	0.274	0.390	0.295	0.440	0.403	0.264	0.277	0.229	0.394
N	169	160	120	151	146	80	80	80	80

Notes: Heteroskedasticity robust standard errors appear underneath coefficient estimates in parentheses. Significance levels are indicated by † $p < 0.1$, * $p < 0.05$ and ** $p < 0.01$. The baseline sample is the full sample with statistical outliers excluded (identified by Cook's distance as described in the main text). The statistical outliers include: Afghanistan, Australia, Bhutan, Congo (Kinshasa), Cyprus, Mongolia, North Korea, Singapore, and Tajikistan. Subsequent sub-samples (3 through 7) take the baseline sample as their starting point. OPEC membership is determined by a country's membership status in 2000. Former Soviets are countries in 2000 that were historically part of the U.S.S.R. The high income sub-sample includes countries whose year 2000 real income per capita is above the median in 2000; the low income sample includes countries whose income is below the median. The high urbanization rate in 1730 sub-sample includes countries whose urbanization rate is above the median in 1730; the low urbanization rate in 1730 sub-sample includes countries whose urbanization rate is below the median in 1730. *N* denotes the number of countries in the cross-sectional sample.

Table 3: Additional Geographic Controls
Dependent variable is Logged Real GDP per capita in 2000

Explanatory Variable / Statistic	1	2	3	4	5	6	7	8
Mean Temp., 1970-1999	0.329	0.514	0.467	0.584†	0.444	0.509	0.416	0.457
	(0.332)	(0.315)	(0.345)	(0.325)	(0.330)	(0.330)	(0.305)	(0.302)
Mean Temp., 1890-1969	1.885†	1.345	1.277	0.790	0.583	0.997	0.846	1.188
	(0.912)	(0.943)	(0.901)	(0.896)	(0.842)	(0.904)	(0.844)	(0.883)
Mean Temp., 1810-1889	-3.995**	-3.964**	-4.134**	-3.675**	-3.335**	-3.825**	-2.669**	-2.884**
	(0.579)	(0.661)	(0.676)	(0.698)	(0.555)	(0.613)	(0.665)	(0.759)
Mean Temp., 1730-1809	1.812**	2.055**	2.335**	2.244**	2.276**	2.292**	1.401*	1.245†
	(0.538)	(0.540)	(0.521)	(0.570)	(0.512)	(0.527)	(0.604)	(0.645)
Abs. Latitude	0.042**						0.021	0.027†
	(0.013)						(0.015)	(0.015)
Elevation (m)		-0.000378**					-0.000201†	-0.000197†
		(0.000136)					(0.000105)	(0.000113)
Precipitation (mm)			0.000095				0.000045	0.000053
			(0.00013)				(0.00013)	(0.00015)
Landlocked Indic.				-0.497**			-0.233	-0.274
				(0.176)			(0.179)	(0.178)
Americas Indic.					0.025		0.197	
					(0.179)		(0.201)	
Sub-Saharan Africa Indic.					-1.052**		-0.759**	
					(0.207)		(0.257)	
Continent Indicators						YES		YES
R^2	0.437	0.426	0.402	0.414	0.524	0.513	0.556	0.556
N	160	160	158	160	160	160	158	158

Notes: Heteroskedasticity robust standard errors appear underneath coefficient estimates in parentheses. Significance levels are indicated by † $p < 0.1$, * $p < 0.05$ and ** $p < 0.01$. The sample considered is the baseline sample. See table 2 and the main text for descriptions of the variables. N denotes the number of countries in the cross-sectional sample.

Table 4: Historic Climate and Openness
Dependent variable is Logged Real GDP per capita in 2000

Explanatory Variable / Statistic	Baseline Sample	Americas Excluded	Sub-Saharan Africa Excluded	Baseline Sample	Americas Excluded	Sub-Saharan Africa Excluded	Baseline Sample	Americas Excluded	Sub-Saharan Africa Excluded
Mean Temp., 1970-1999	0.351	0.454	0.262	0.489	0.462	0.509	0.379	0.467	0.346
	(0.320)	(0.357)	(0.371)	(0.347)	(0.386)	(0.383)	(0.322)	(0.350)	(0.369)
Mean Temp., 1890-1969	0.755	1.219	0.673	1.207	1.532	0.811	0.438	0.551	0.196
	(0.780)	(0.966)	(0.781)	(0.926)	(1.136)	(0.916)	(0.812)	(1.018)	(0.872)
Mean Temp., 1810-1889	-3.591**	-4.168**	-3.028**	-4.239**	-3.886**	-3.290**	-3.214**	-2.872**	-2.452**
	(0.599)	(0.802)	(0.558)	(0.741)	(0.913)	(0.679)	(0.684)	(0.871)	(0.663)
Mean Temp., 1730-1809	2.539**	2.53**	2.136**	2.564**	2.569**	2.107**	2.797**	2.778**	2.34**
	(0.540)	(0.580)	(0.532)	(0.528)	(0.547)	(0.531)	(0.534)	(0.544)	(0.534)
Log Population in 1730	0.034	0.239	0.020				0.043	0.022	0.023
	(0.050)	(0.055)	(0.047)				(0.053)	(0.061)	(0.051)
Temp., 1730-1809 × Log Pop. in 1730	-0.006*	-0.005†	-0.004†				-0.006*	-0.005†	-0.005*
	(0.002)	(0.003)	(0.002)				(0.003)	(0.003)	(0.002)
Log Inv. Dist. in 1730				-0.146	-1.337	-0.457	-0.676	-1.659†	-0.886†
				(0.522)	(0.930)	(0.493)	(0.513)	(0.902)	(0.496)
Temp., 1730-1809 × Log Inv. Dist. in 1730				0.008	0.086*	0.019	0.038	0.103*	0.043†
				(0.024)	(0.043)	(0.023)	(0.024)	(0.042)	(0.024)
R^2	0.480	0.498	0.368	0.391	0.487	0.300	0.491	0.559	0.390
N	160	128	120	160	128	120	160	128	120

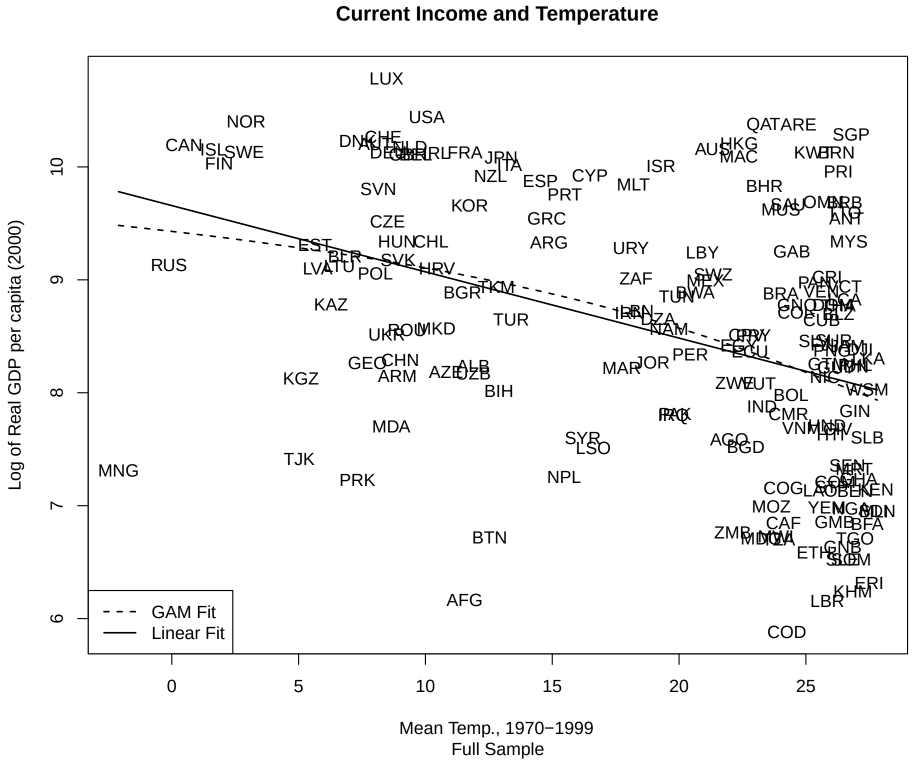
Notes: Heteroskedasticity robust standard errors appear underneath the coefficient estimates in parentheses. Significance levels are indicated by † $p < 0.10$, * $p < 0.05$ and ** $p < 0.01$. Population in 1730 and the historic openness measure are calculated from the HYDE database, version 3.1 (see the main text for full details). The × indicates a variable interaction (a product of the two components). N denotes the number of countries in the cross-sectional sample.

Table 5: Historic Climate and Openness
Dependent variable is Agricultural Value-Added over GDP in 2000

Explanatory Variable / Statistic	Baseline Sample	Americas Excluded	Sub-Saharan Africa Excluded	Baseline Sample	Americas Excluded	Sub-Saharan Africa Excluded	Baseline Sample	Americas Excluded	Sub-Saharan Africa Excluded
Mean Temp., 1970-1999	-7.592	-8.586	-1.841	-8.930	-8.768	-4.903	-7.904	-9.153	-3.030
	(5.289)	(5.739)	(5.241)	(5.317)	(5.951)	(5.210)	(5.275)	(5.764)	(5.192)
Mean Temp., 1890-1969	5.228	-3.252	7.660	2.101	-5.677	6.682	8.271	3.312	11.344
	(11.223)	(12.658)	(11.586)	(12.998)	(15.864)	(14.557)	(12.273)	(14.955)	(14.009)
Mean Temp., 1810-1889	44.713**	53.977**	29.701**	46.256**	45.450**	28.526**	37.703**	37.94**	22.386*
	(9.127)	(10.925)	(7.213)	(10.571)	(11.911)	(10.605)	(9.927)	(12.074)	(9.676)
Mean Temp., 1730-1809	-43.778**	-43.256	-36.967**	-39.248**	-39.732**	-30.612**	-42.818**	-44.053**	-34.140**
	(8.882)	(9.422)	(8.217)	(9.406)	(9.360)	(9.237)	(9.259)	(9.132)	(9.017)
Log Population in 1730	-1.152**	-1.042†	-1.117*				-1.060*	-0.929	-0.867†
	(0.433)	(0.563)	(0.446)				(0.494)	(0.678)	(0.479)
Temp., 1730-1809 × Log Pop. in 1730	0.091**	0.079*	0.081**				0.088**	0.082*	0.068*
	(0.024)	(0.036)	(0.026)				(0.027)	(0.037)	(0.026)
Log Inv. Dist. in 1730				4.607	21.406†	6.221	10.451	24.341*	9.453
				(6.647)	(11.855)	(6.760)	(6.862)	(11.780)	(7.031)
Temp., 1730-1809 × Log Inv. Dist. in 1730				-0.030	-1.086†	-0.062	-0.398	-1.265*	-0.271
				(0.334)	(0.608)	(0.343)	(0.354)	(0.608)	(0.360)
R^2	0.318	0.353	0.253	0.270	0.351	0.248	0.329	0.388	0.290
N	153	121	111	153	121	111	153	121	111

Notes: Heteroskedasticity robust standard errors appear underneath the coefficient estimates in parentheses. Significance levels are indicated by † $p < 0.10$, * $p < 0.05$ and ** $p < 0.01$. Population in 1730 and the historic openness measure are calculated from the HYDE database, version 3.1 (see the main text for full details). The × indicates a variable interaction (a product of the two components). N denotes the number of countries in the cross-sectional sample.

Figure 1


Current Income and Temperature
Log of Real GDP per capita (2000)
Mean Temp., 1970−1999
Full Sample
GAM Fit
Linear Fit
0
5
10
15
20
25
6
7
8
9
10

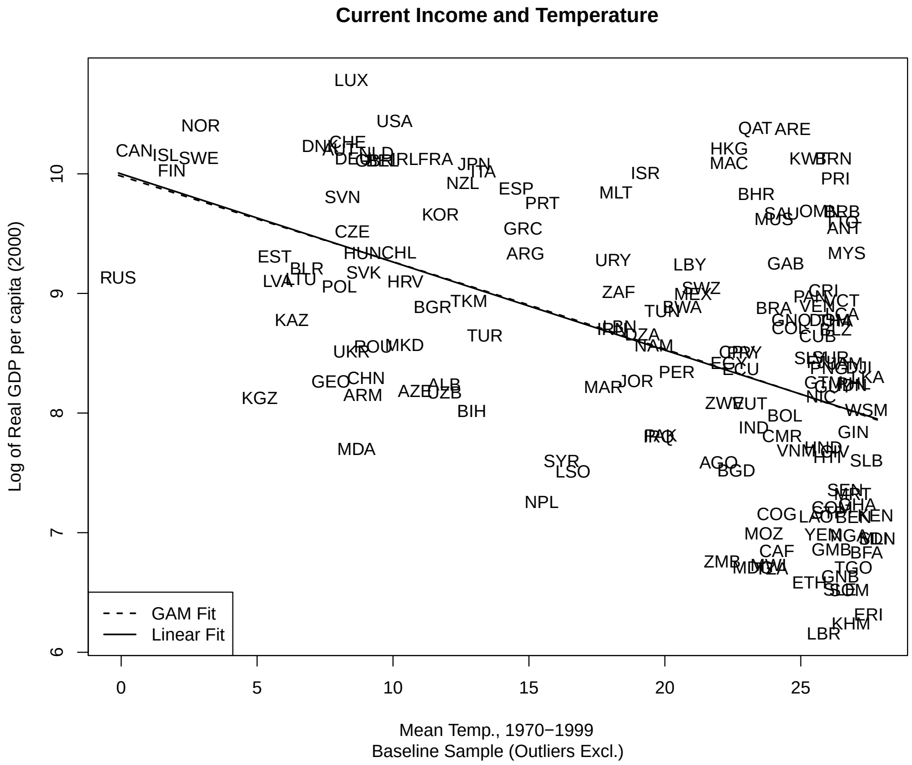
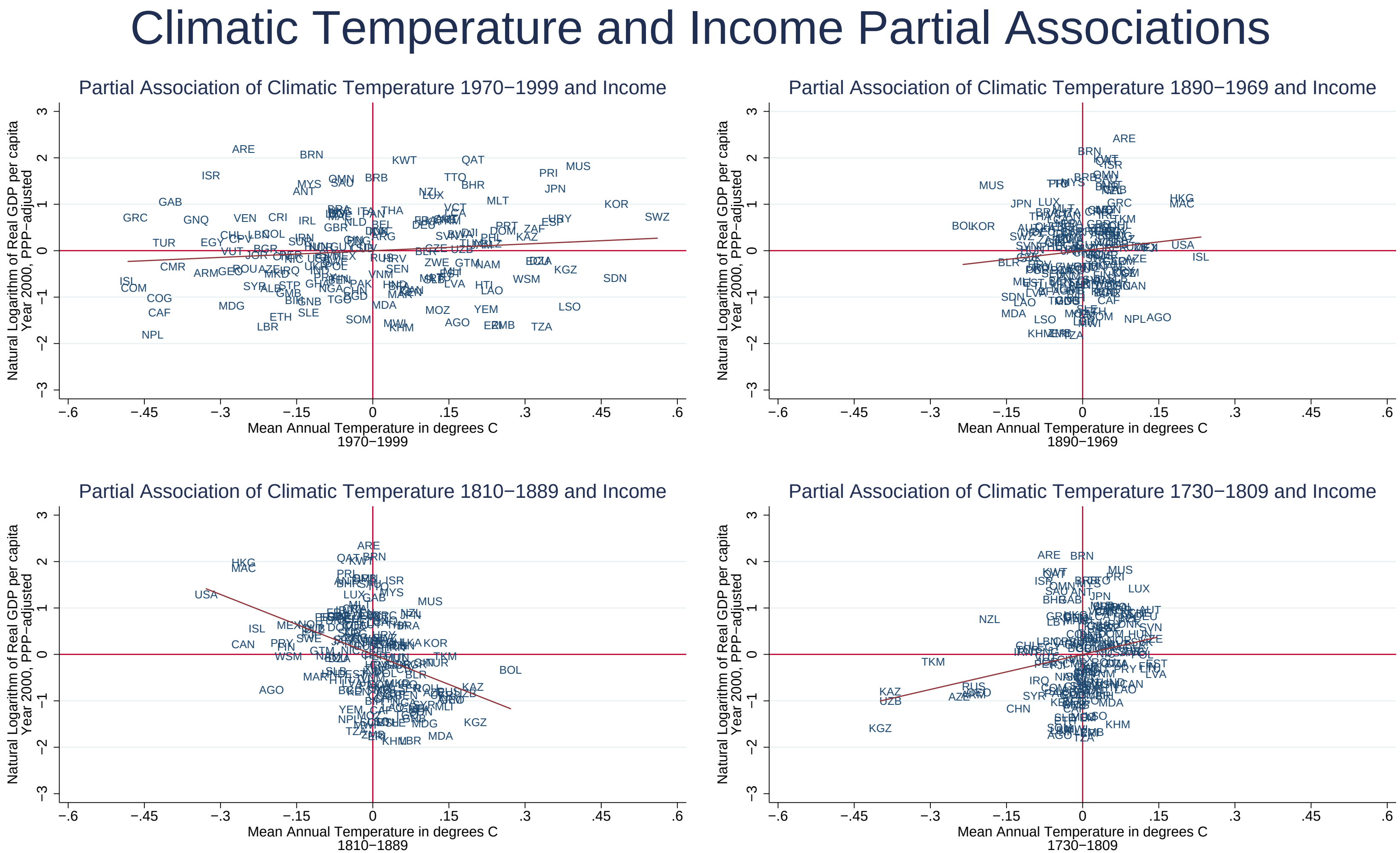
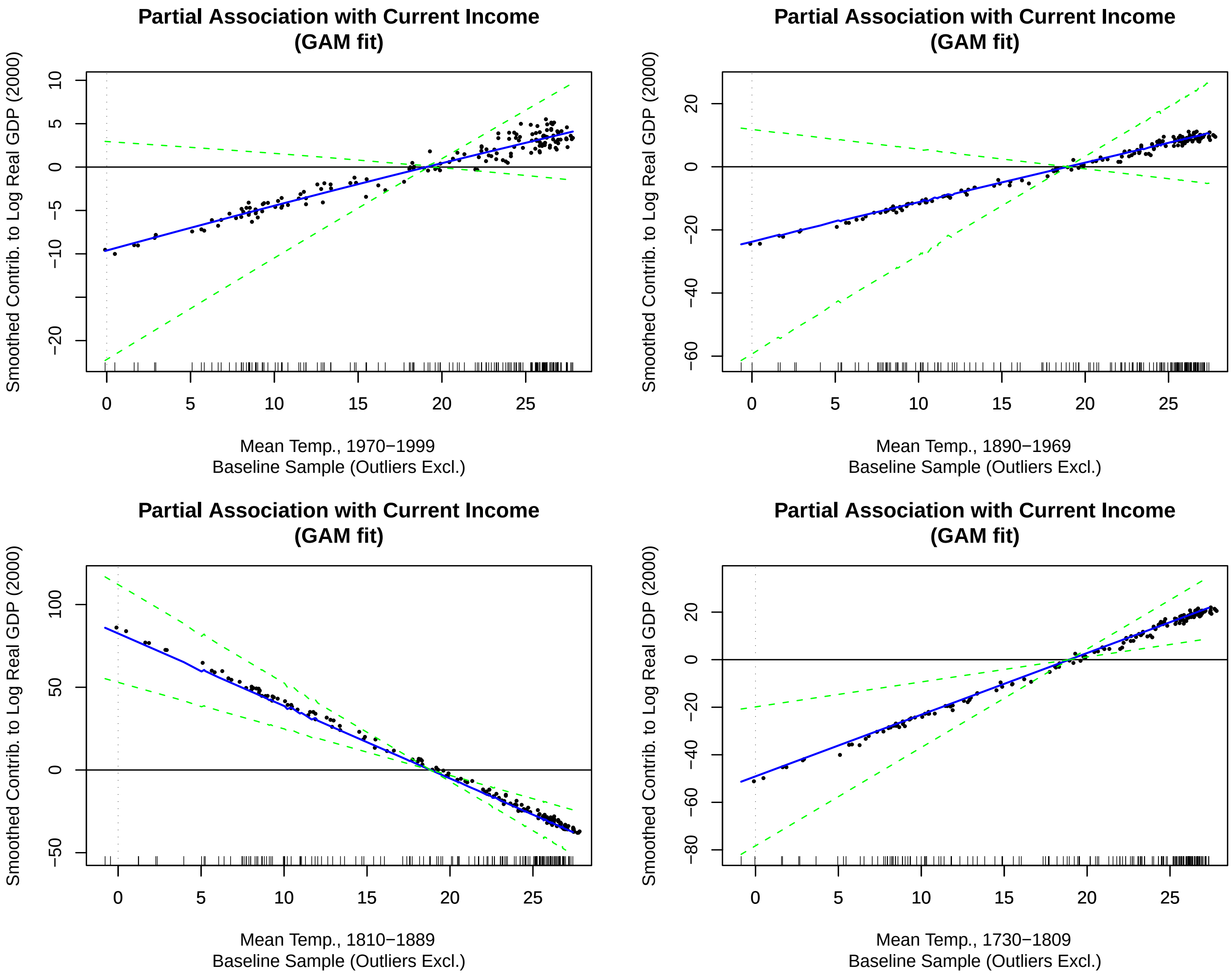

Current Income and Temperature
Log of Real GDP per capita (2000)
Mean Temp., 1970−1999
Baseline Sample (Outliers Excl.)
GAM Fit
Linear Fit
0
5
10
15
20
25
6
7
8
9
10

Figure 2



The panels depict the partial associations (residual scatterplots) between the listed variables under the specification in regression 2. Plots reflect the Baseline Sample (Outliers Excl.).

Figure 3



Partial Association with Current Income
(GAM fit)
Smoothed Contrib. to Log Real GDP (2000)
Mean Temp., 1970−1999
Baseline Sample (Outliers Excl.)
Partial Association with Current Income
(GAM fit)
Smoothed Contrib. to Log Real GDP (2000)
Mean Temp., 1890−1969
Baseline Sample (Outliers Excl.)
Partial Association with Current Income
(GAM fit)
Smoothed Contrib. to Log Real GDP (2000)
Mean Temp., 1810−1889
Baseline Sample (Outliers Excl.)
Partial Association with Current Income
(GAM fit)
Smoothed Contrib. to Log Real GDP (2000)
Mean Temp., 1730−1809
Baseline Sample (Outliers Excl.)

Table A.1: Data Sources

Data Source	*Access Location*	*Component/Variable*
Gallup, Sachs, and Mellinger (1999) Geography and Development Dataset	URL: http://www.cid.harvard.edu /ciddata/geodata.dta. Downloaded on 6 October 2009.	LANDLOCK: Indicator for whether or not a country is landlocked (no direct access to the sea) in 2000.
History Database of the Global Environment (HYDE), v. 3.1	URL: ftp://ftp.mnp.nl/hyde /hyde31˙final/*_pop.zip. Downloaded on 6 August 2009. Version from 26 June 2009.	Global 5 minute gridded population counts (raster) for 1730, 1830, 1970, and 2000. Each year is a separate ASCII file.
ISO 3166 Country Codes	URL: http://www.iso.org /iso/country˙codes.htm. Accessed on 15 October 2008.	2 and 3 letter country codes, used in harmonization of datasets.
Mann, Bradley, and Hughes (1998, 2004) Global Gridded Temperature Anomalies, 1730-1993	URL: http://picasso.ngdc.noaa.gov /paleo/data/mann/mann*.dat. Downloaded on 18 January 2008. Version from 2004.	Global 5 degree gridded annual temperature anomalies raster file (degrees Celsius). Each year is a separate ASCII file.
Organization of the Petroleum Exporting Countries (OPEC) Website	URL: http://www.opec.org/library /faqs/aboutopec/q3.htm. Accessed on 5 August 2009.	Country OPEC Membership in 2000.
Penn World Table v.6.2	URL: http://pwt.econ.upenn.edu /php˙site/pwt62/pwt62_form.php. Downloaded on 27 July 2009. Version from September 2006.	RGDPL: Country Real GDP (Income) per capita, in constant 2000 international dollars (Laspeyres), in 2000 and over 1980-2000. RGDPWOK: Country Real GDP (Income) per worker, in constant 2000 international dollars (Chained), in 2000.
United States Geological Survey (USGS) Global GIS Global Coverage DVD-ROM, 2003	Distributed by the American Geological Institute (AGI). Described at URL: http://webgis.wr.usgs.gov /globalgis/index.html.	Country boundaries vector file (admin02.shp), with WGS1984 datum and geographic projection. Global 5 degree latitude-longitude grid vector file (latlong.shp), with WGS1984 datum and geographic projection. Elevation: average elevation within 100 kilometers of the population centroid (or nearest point on land for non-convex countries). Calculated from the file image˙pnt1.shp.
University of East Anglia Climatic Research Unit Global Gridded Temperature, 1850-2009	URL: http://hadobs.metoffice.com /crutem3/data/CRUTEM3.nc. Downloaded on 2 February 2008.	Global 5 degree gridded monthly temperature anomalies raster-NetCDF file (degrees Celsius).
	URL: http://www.cru.uea.ac.uk /cru/data/temperature /ftpdata/absolute.nc. Downloaded on 2 February 2008.	Global 5 degree gridded monthly average temperature level over 1961-1990, raster-NetCDF file (degrees Celsius).
Wilmott and Matsuura's June 2009 gridded global temperature series	URL: http://climate.geog.udel.edu /˜climate/html˙pages /download.html#P2009. Downloaded on 10 February 2010	Precipitation (mm)
World Bank Country Classification	URL: http://www.worldbank.org /data /countryclass/classgroups.htm. Accessed on 5 August 2009.	Country geographic regions (Sub-Saharan Africa, Latin America and the Caribbean).
World Development Indicators, 2010 edition	URL: http://http://www.esds.ac.uk /international. Accessed on 21 May 2010.	Agric. Value-Added over GDP in 2000 (variable code NV.AGR.TOTL.ZS)

Table A.2: Full Sample of Countries

Country Name	*ISO 3166-1 2-Letter Code*	*ISO 3166-1 3-Letter Code*	*Income Group*
Afghanistan	AF	AFG	Low Income
Albania	AL	ALB	Low Income
Algeria	DZ	DZA	High Income
Angola	AO	AGO	Low Income
Argentina	AR	ARG	High Income
Armenia	AM	ARM	Low Income
Australia	AU	AUS	High Income
Austria	AT	AUT	High Income
Azerbaijan	AZ	AZE	Low Income
Bahrain	BH	BHR	High Income
Bangladesh	BD	BGD	Low Income
Barbados	BB	BRB	High Income
Belarus	BY	BLR	High Income
Belgium	BE	BEL	High Income
Belize	BZ	BLZ	High Income
Benin	BJ	BEN	Low Income
Bhutan	BT	BTN	Low Income
Bolivia	BO	BOL	Low Income
Bosnia and Herzegovina	BA	BIH	Low Income
Botswana	BW	BWA	High Income
Brazil	BR	BRA	High Income
Brunei Darussalam	BN	BRN	High Income
Bulgaria	BG	BGR	High Income
Burkina Faso	BF	BFA	Low Income
Cambodia	KH	KHM	Low Income
Cameroon	CM	CMR	Low Income
Canada	CA	CAN	High Income
Cape Verde	CV	CPV	Low Income
Central African Republic	CF	CAF	Low Income
Chile	CL	CHL	High Income
China	CN	CHN	Low Income
Colombia	CO	COL	High Income
Comoros	KM	COM	Low Income
Congo	CG	COG	Low Income
Congo Kinshasa	CD	COD	Low Income
Costa Rica	CR	CRI	High Income
Croatia	HR	HRV	High Income
Cuba	CU	CUB	High Income
Cyprus	CY	CYP	High Income
Czech Republic	CZ	CZE	High Income
Denmark	DK	DNK	High Income
Djibouti	DJ	DJI	Low Income
Dominican Republic	DO	DOM	High Income
Ecuador	EC	ECU	Low Income
Egypt	EG	EGY	Low Income
El Salvador	SV	SLV	Low Income
Equatorial Guinea	GQ	GNQ	High Income
Eritrea	ER	ERI	Low Income
Estonia	EE	EST	High Income
Ethiopia	ET	ETH	Low Income
Fiji	FJ	FJI	Low Income
Finland	FI	FIN	High Income
France	FR	FRA	High Income
Gabon	GA	GAB	High Income
Gambia	GM	GMB	Low Income
Georgia	GE	GEO	Low Income
Germany	DE	DEU	High Income
Ghana	GH	GHA	Low Income
Greece	GR	GRC	High Income
Guatemala	GT	GTM	Low Income

Country Name	*ISO 3166-1 2-Letter Code*	*ISO 3166-1 3-Letter Code*	*Income Group*
Guinea	GN	GIN	Low Income
Guinea-Bissau	GW	GNB	Low Income
Guyana	GY	GUY	Low Income
Haiti	HT	HTI	Low Income
Honduras	HN	HND	Low Income
Hong Kong	HK	HKG	High Income
Hungary	HU	HUN	High Income
Iceland	IS	ISL	High Income
India	IN	IND	Low Income
Indonesia	ID	IDN	Low Income
Iran, Islamic Republic of	IR	IRN	High Income
Iraq	IQ	IRQ	Low Income
Ireland	IE	IRL	High Income
Israel	IL	ISR	High Income
Italy	IT	ITA	High Income
Ivory Coast	CI	CIV	Low Income
Jamaica	JM	JAM	Low Income
Japan	JP	JPN	High Income
Jordan	JO	JOR	Low Income
Kazakhstan	KZ	KAZ	High Income
Kenya	KE	KEN	Low Income
Korea, Dem. People's Republic of (North Korea)	KP	PRK	Low Income
Korea, Republic of (South Korea)	KR	KOR	High Income
Kuwait	KW	KWT	High Income
Kyrgyzstan	KG	KGZ	Low Income
Lao People's Dem. Republic	LA	LAO	Low Income
Latvia	LV	LVA	High Income
Lebanon	LB	LBN	High Income
Lesotho	LS	LSO	Low Income
Liberia	LR	LBR	Low Income
Libyan Arab Jamahiriya	LY	LBY	High Income
Lithuania	LT	LTU	High Income
Luxembourg	LU	LUX	High Income
Macao	MO	MAC	High Income
Macedonia, the former Yugoslav Republic of	MK	MKD	High Income
Madagascar	MG	MDG	Low Income
Malawi	MW	MWI	Low Income
Malaysia	MY	MYS	High Income
Mali	ML	MLI	Low Income
Malta	MT	MLT	High Income
Mauritania	MR	MRT	Low Income
Mauritius	MU	MUS	High Income
Mexico	MX	MEX	High Income
Moldova	MD	MDA	Low Income
Mongolia	MN	MNG	Low Income
Morocco	MA	MAR	Low Income
Mozambique	MZ	MOZ	Low Income
Namibia	NA	NAM	High Income
Nepal	NP	NPL	Low Income
Netherlands	NL	NLD	High Income
Netherlands Antilles	AN	ANT	High Income
New Zealand	NZ	NZL	High Income
Nicaragua	NI	NIC	Low Income
Nigeria	NG	NGA	Low Income
Norway	NO	NOR	High Income
Oman	OM	OMN	High Income
Pakistan	PK	PAK	Low Income
Panama	PA	PAN	High Income
Papua New Guinea	PG	PNG	Low Income
Paraguay	PY	PRY	Low Income

Country Name	*ISO 3166-1 2-Letter Code*	*ISO 3166-1 3-Letter Code*	*Income Group*
Peru	PE	PER	Low Income
Philippines	PH	PHL	Low Income
Poland	PL	POL	High Income
Portugal	PT	PRT	High Income
Puerto Rico	PR	PRI	High Income
Qatar	QA	QAT	High Income
Romania	RO	ROU	Low Income
Russian Federation	RU	RUS	High Income
Saint Lucia	LC	LCA	High Income
Saint Vincent and the Grenadines	VC	VCT	High Income
Samoa	WS	WSM	Low Income
Sao Tome and Principe	ST	STP	Low Income
Saudi Arabia	SA	SAU	High Income
Senegal	SN	SEN	Low Income
Sierra Leone	SL	SLE	Low Income
Singapore	SG	SGP	High Income
Slovakia	SK	SVK	High Income
Slovenia	SI	SVN	High Income
Solomon Islands	SB	SLB	Low Income
Somalia	SO	SOM	Low Income
South Africa	ZA	ZAF	High Income
Spain	ES	ESP	High Income
Sri Lanka	LK	LKA	Low Income
Sudan	SD	SDN	Low Income
Suriname	SR	SUR	Low Income
Swaziland	SZ	SWZ	High Income
Sweden	SE	SWE	High Income
Switzerland	CH	CHE	High Income
Syrian Arab Republic	SY	SYR	Low Income
Tajikistan	TJ	TJK	Low Income
Tanzania, United Republic of	TZ	TZA	Low Income
Thailand	TH	THA	High Income
Togo	TG	TGO	Low Income
Trinidad and Tobago	TT	TTO	High Income
Tunisia	TN	TUN	High Income
Turkey	TR	TUR	High Income
Turkmenistan	TM	TKM	High Income
Ukraine	UA	UKR	Low Income
United Arab Emirates	AE	ARE	High Income
United Kingdom	GB	GBR	High Income
United States	US	USA	High Income
Uruguay	UY	URY	High Income
Uzbekistan	UZ	UZB	Low Income
Vanuatu	VU	VUT	Low Income
Venezuela	VE	VEN	High Income
Vietnam	VN	VNM	Low Income
Yemen	YE	YEM	Low Income
Zambia	ZM	ZMB	Low Income
Zimbabwe	ZW	ZWE	Low Income

Notes: These countries constitute the full sample. They are countries for which real income per capita in 2000 from the Penn World v. 6.2 exists and for which current and historic temperatures can be calculated. The ISO 3166-1 country codes have been adapted in some cases to accommodate the availability of income data in the Penn World table (e.g., Hong Kong is available separately). High income indicates countries whose year 2000 real income per capita is above the median income in 2000; low income sample includes countries whose income is below the median.