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Income and Temperatures

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Income and Temperature

1. Introduction

Nordhaus (2006) insightfully points out:

> *"The linkage between economic activity and geography is obvious to most people: populations cluster mainly on coasts and rarely on ice sheets. Yet, modern macroeconomics and growth economics generally ignore geographic factors such as climate, proximity to water, soils, tropical pests, and permafrost."(page 3510)*

This paper intends to narrow this gap. Specifically, we focus on the relationship between temperature (a climate factor) and income (GDP per capita). This relationship is important for two reasons. First, it may complement the standard economic theory to better explain cross-sectional differences in income. Sachs (2003), Acemoglu et al. (2002), and Rodrik et al. (2004) explain why, in theory, temperature may affect economic growth, directly or indirectly. Second, it may enable economists to estimate the potential impact of global warming without assuming a structural model. The structural-model approach, commonly known as the Integrated Assessment Model (IAM), has one major challenge in its complexity.[2] In contrast, the cross-sectional relationship between temperature and income motivates a simple reduced-form approach. One prominent example of using this relationship to estimate the impact of global warming is the work of Horowitz (2009).

Until recently, empirical evidence generally suggests that there is a negative relationship between temperature and income. This negative relationship was first documented in the eighteenth century by Montesquieu (1750) and about one and a half centuries later by Huntington (1915), and has been confirmed by many more recent studies (e.g. Kamarck 1976, Theil and Chen 1995, Ram 1997, Horowitz 2009, and Dell et al. 2008, 2009). One implication of this (negative) relationship is that global warming has an adverse impact on economic activity. Horowitz (2009) empirically estimates the cross-sectional relationship between income and temperature using country-level international data. Based on his parameter estimates, he argues that the adverse impact of an increase of 1 degree Celsius in temperature due to global warming can result in as much as a 3.8% decrease in world GNP.

However, a recent empirical study by Nordhaus (2006) presents a challenge to the literature. He finds that the temperature-income relationship depends on how researchers measure income. If income is measured by income per capita (the typical measurement used in the literature), the relationship is negative; however, if income is measured by income per area (income/km^2), the relation becomes positive.[3] His "climate-output reversal" findings (page 3513) suggest that the impact of global warming may be positive if we focus on income per area, which according to him is a more appropriate income measurement from a geographic and ecological point of view.

Nevertheless, Dell et al. (2008) point out that the simple relationship between temperature and income (as in Nordhaus, 2006) may be spurious and suffer from an omitted-variables problem. Our current paper is motivated by this insight. We show in this paper that the results of Nordhaus (2006) may be due to a model misspecification or an omitted-variable problem. Based on a temperature-income

[2] Dell, Jones, and Olken (2008) point out that "A fundamental challenge for this enumerative approach is complexity: the set of candidate mechanisms through which climate may influence economic outcomes is extremely large and, even if each mechanism could be enumerated and its operation understood, how they interact and aggregate to shape macroeconomic outcomes raises additional difficulties." (page 1) Mendelsohn et al. (2000), Nordhaus and Boyer (2000) and Tol (2002), among others, use the structural approach to investigate the impact of global warming.

[3] Nordhaus (2006) does not provide a satisfactory explanation for why the income-temperature relationship is sensitive to the income measurement.

model that is well motivated by the theory on how temperature affects income, we find that the relationship between temperature and income is *not* dependent on income measurement and is always negative. Our parameter estimates suggest that the adverse impact of a 3 degrees Celsius increase in temperature (due to global warming) can result in as much as a 9% decrease in income for developed nations such as the United States and the United Kingdom. Our findings therefore confirm previous studies, and suggest a more aggressive climate mitigation policy.

The remainder of the paper is organized as follows: Section 2 presents our model. Section 3 describes the data. Section 4 reports our empirical results. Section 5 concludes the manuscript.

2. A Model of Temperature and Income

The literature has proposed many possible linkages between temperature and income. Acemoglu et al. (2002), Easterly and Levine (2002), and Rodrik et al. (2004) emphasize the indirect historical effects of temperature on income (through institutions). In contrast, Gallup et al. (1998), Mellinger et al. (2000), Gallup and Sachs (2001), Sachs and Malaney (2002), and Sachs (2003) stress the importance of direct contemporaneous effects of temperature on income.[4]

Recent empirical studies suggest that temperature may affect income through both its historical indirect effects and its contemporaneous direct effects. For instance, Horowitz (2009) finds that the income-temperature relationship holds among countries with similar institutional structure (e.g. the OECD countries); Dell et al. (2009) show that this relationship also exists within counties and within states within countries; Dell et al. (2008) further document strong short-run effects of temperature on economic growth.[5]

Thus, a complete economic model should take into account both historical and contemporaneous effects of temperature on income as well as the effects of other relevant economic variables such as population growth and capital accumulation. We build a model of income and temperature based on this notion. Specifically, we consider a Cobb-Douglas type production function[6]:

$$Y_i = e^{\varepsilon_i} e^{\delta T_i} A_i(T_i) K_i^{\alpha} L_i^{\beta} \tag{1a}$$

where Y_i is the total income (output), A_i represents productivity which is a function of temperature T_i, K_i represents capital, L_i stands for labor, ε_i captures the effects of all other variables (for instance the geographic variables in Nordhaus, 2006), and $\alpha,\ \beta < 1$. Since we allow productivity (A_i) to depend on temperature, this model captures the historical effect of temperature on institutions. Since temperature

[4] Sachs (2003) points out that in principle historical effects should not be the only driving force of the income-temperature relationship "since many of the reasons why geography seems to have affected institutional choices in the past …… are indeed based on direct effects of geography on production systems, human health, and environmental sustainability, and many of those very same channels would still be likely to apply today."(page 2)

[5] They find that in poor countries over the 1950-2003 period, a one degree Celsius rise in temperature in a given year reduced economic growth in that year by 1.1 percentage points.

[6] Choinière and Horowitz (2006) also consider a Cobb-Douglas type production function. They model temperature as a factor of production. However, if temperature negatively affects output, it does not seem to fit the economics definition of factors of production. Therefore, we follow Dell, Jones, and Olken (2008) and model temperature differently from labor and capital.

also directly affects output through the second term, this model also captures the contemporaneous effect of temperature. Please note that it is this direct contemporaneous effect (δ) that is of interest to us, because it is relevant for assessing the impact of global warming (see Horowitz, 2009).

Let $K_i = \nu_i L_i$ where ν_i is capital-labor ratio, $L_i = o_i P_i$ where o_i represents labor participation rate and P_i represents population. Then we have,

$$Y_i = \nu_i^{\alpha} o_i^{\alpha+\beta} e^{\varepsilon_i} e^{\delta T_i} A_i(T_i) P_i^{\alpha+\beta} \tag{2}$$

We can measure income by output per person as in most studies in the literature:

$$\frac{Y_i}{P_i} = \nu_i^{\alpha} o_i^{\alpha+\beta} e^{\varepsilon_i} e^{\delta T_i} A_i(T_i) P_i^{\alpha+\beta-1} \tag{3a}$$

or output per area as in Nordhaus (2006):

$$\frac{Y_i}{S_i} = \nu_i^{\alpha} o_i^{\alpha+\beta} e^{\varepsilon_i} e^{\delta T_i} A_i(T_i) P_i^{\alpha+\beta} S_i^{-1} \tag{3b}$$

where S_i represents area. Taking log on both sides, we have

$$\log(\frac{Y_i}{P_i}) = \log(\nu_i^{\alpha} o_i^{\alpha+\beta} A_i(T_i)) + (\alpha + \beta - 1)\log(P_i) + \delta T_i + \varepsilon_i \tag{4a}$$

or

$$\log(\frac{Y_i}{S_i}) = \log(\nu_i^{\alpha} o_i^{\alpha+\beta} A_i(T_i)) + (\alpha + \beta)\log(P_i) - \log(S_i) + \delta T_i + \varepsilon_i \tag{4b}$$

Since the capital-labor ratio, the labor participation rate, and the temperature's historical effect on productivity (A_i) may be country-specific, we use country dummy variables (d_i) as proxies for $\log(\nu_i^{\alpha} o_i^{\alpha+\beta} A_i(T_i))$. As a result, we have

$$\log(\frac{Y_i}{P_i}) = \phi d_i + (\alpha + \beta - 1)\log(P_i) + \delta T_i + \varepsilon_i \tag{5a}$$

or

$$\log(\frac{Y_i}{S_i}) = \phi d_i + (\alpha + \beta)\log(P_i) - \log(S_i) + \delta T_i + \varepsilon_i \tag{5b}$$

where φ is the row vector of country coefficients for the column vector of country dummy variables d_i .

We can gain two important insights from this model (equations 5a and 5b). First, this model shows that regardless of whether we look at output per capita or output per area, the direct effect of temperature on output should be the same, δ , and not dependent on income measurement. Again, we emphasize that it is this direct contemporaneous effect (δ) that we are really interested in. In fact, the coefficient estimate should also be the same if we directly estimate the following production function:

$$\log(Y_i) = d_i + (\alpha + \beta)\log(P_i) + \delta T_i + \varepsilon_i \qquad (6)$$

Second, if we drop population or area in the empirical estimations, our coefficient estimates of temperature may be biased. In many previous studies including Horowitz (2009) and Nordhaus (2006), economic variables such as population are usually dropped in empirical estimations. From Equation (5a) we can see that when we use income per capita as the dependent variable, dropping population will not cause bias when $\alpha + \beta = 1$ (the production function has constant returns to scale). Since this may be true (at least approximately) for most economies, dropping labor in the income-per-capita regressions may not result in much bias. Another situation where dropping labor will not cause bias in the estimate is when labor is orthogonal to the included independent variables, which is very unlikely. On the other hand, if we use income per area as the dependent variable as in Equation (5b), dropping labor can bias the estimates. We can see from Equation (5b) that dropping labor essentially requires using area as a proxy for population, which most likely will cause biases because the correlation between area and population is usually weak (in our sample the correlation is only about 0.2). Furthermore, dropping population will force temperature to pick up the effect of population. There is a voluminous literature on how temperature positively affects population growth (see Lee, Fok and Zhang, 2008 among others). If temperature is positively related to population, and population positively affects output per area, dropping population may reverse the sign of the estimated temperature coefficient in Equation (5b). We will explore in this paper whether this explains the puzzling findings in Nordhaus (2006).

To model potential nonlinear effects of temperature on income empirically, we follow the relevant literature (e.g. Horowitz, 2009, and Nordhaus, 2006) and use a cubic polynomial in temperature in our econometric models. Therefore, our empirical regression models are

$$\log(\frac{Y_i}{P_i}) = \varphi d_i + a_1 T_i + a_2 T_i^2 + a_3 T_i^3 + b\log(P_i) + e_i \qquad (7a)$$

and

$$\log(\frac{Y_i}{S_i}) = \tilde{\varphi} d_i + \tilde{a}_1 T_i + \tilde{a}_2 T_i^2 + \tilde{a}_3 T_i^3 + \tilde{b}\log(P_i) + \tilde{c}\log(S_i) + e_i \qquad (7b)$$

3. Data

In this paper, we use a geophysically-scaled economic data set (G-Econ) developed by Nordhaus (2006). The G-Econ data estimate gross output at a 1-degree longitude by 1-degree latitude resolution at a global scale, and therefore allow a cell-level analysis of the relationship between temperature and income.

There are several advantages of using cell-level data compared to using national-level data for studying the income-temperature relationship. Most important, using cell-level data rather than national-level data makes temperature measurement more meaningful. As Nordhaus (2006) concisely points out, “for many countries, averages of most geographic variables (such as temperature or distance from seacoast) cover such a huge area that they are virtually meaningless, whereas for most grid cells the averages cover a reasonably small area.” (Page 3511) Furthermore, using cell-level data makes the number of useful observations increase from around 100 countries to about 15,000 terrestrial cells. Additionally, because the data set has multiple observations per country, it is possible to control for factors that are unique to individual countries, which is important for our model discussed in section 2. Finally, it also makes our results comparable to those in Nordhaus (2006).

Nordhaus (2006) develops income measurement on “gridded output”, gross cell product (GCP). The conceptual basis of GCP is the same as that of gross domestic product (GDP) as developed in the national income accounts, except that the geographic unit of the latitude-longitude grid cell is used instead of the political boundaries. The globe contains 64,800 such grid cells, of which 27,442 observations have reasonably complete data on climate, population, and output. After removing cells with zero GCP, area, population and data with lower than medium quality, we are left with 14,829 observations. The 1990 output of all countries using national aggregates estimated by the World Bank is converted into a common metric using market exchange rates based on 2000 U.S. dollars. A full description of the data and methods can be found at the project web site (http://gecon.yale.edu).

Table 1 contains summary statistics of the variables used in this paper. Since our sample includes 85 different countries, we use 84 dummy variables altogether in our empirical estimations.

Table 1. Summary Statistics of the Variables used in this paper.

Variable	Abbreviation in G-Econ	Mean	Median	Std. Dev.	Min	Max
GCP (billions of 2000 US$)	GCPMER_1990_211	1.712	0.03297	12.63	$2.59*10^{-9}$	866.2
Population (persons)	POPGPW_1990_211	$2.712*10^{5}$	$7.232*10^{3}$	$9.508*10^{5}$	$1.004*10^{-4}$	$2.640*10^{7}$
Area (km^2)	AREA	6205.996	6186.040	3703.536	1.147	12414.564
Temperature (C^0)	TEMPAV	5.223	5.000	13.6252	-25.880	29.180
Precipitation (mm/month)	PRECAV	61.75	43.63	55.659	0.10	640.89
Elevation (m)	ELEV_F	549.2	277.0	804.3651	-29.0	5409.6

4. Empirical Results

4.1 Main findings

For comparison, we first estimate the empirical models without economic variables as in Nordhaus (2006). That is,

$$\log(\frac{Y_i}{P_i}) = \varphi d_i + a_1 T_i + a_2 T_i^2 + a_3 T_i^3 + e_i \tag{8a}$$

or

$$\log(\frac{Y_i}{S_i}) = \tilde{\varphi} d_i + \tilde{a}_1 T_i + \tilde{a}_2 T_i^2 + \tilde{a}_3 T_i^3 + e_i \tag{8b}$$

The results are summarized in Table 2. We confirm Nordhaus’s (2006) findings in that without economic variables such as population, the temperature-income relationship depends on how income is measured. The estimated coefficient on temperature is equal to -0.028 (*t* = -29.27) if income is measured by income per capita, but a positive 0.345 (*t* = 91.31) if income is measured by income per area.

Table 2. Temperature-Income Relation when Economic Variables are Omitted:

Panel A: $\log(\frac{Y_i}{P_i}) = \phi d_i + a_1 T_i + a_2 T_i^2 + a_3 T_i^3 + e_i$

	T	***T²***	***T³***	***R²***
Coefficient	-0.02846	-0.00035	0.00003	0.9031
***t*-statistics**	-29.27	-9.47	16.79	
***p*-value**	0.0000	0.0000	0.0000	

Panel B: $\log(\frac{Y_i}{S_i}) = \tilde{\varphi} d_i + \tilde{a}_1 T_i + \tilde{a}_2 T_i^2 + \tilde{a}_3 T_i^3 + e_i$

	T	***T²***	***T³***	***R²***
Coefficient	0.34514	-0.00244	-0.00030	0.7365
***t*-statistics**	91.31	-16.66	-35.84	
***p*-value**	0.0000	0.0000	0.0000	

We estimate the empirical models without economic variables as in Nordhaus (2006).

However, as Dell et al. (2008) point out, this simple relationship between temperature and income may be spurious and suffer from an omitted-variable misspecification. We have elaborated upon this in Section 2. That is, estimations can be biased especially for the regression with income per area as the dependent variable, and it is possible that the bias is severe enough to reverse the sign of the temperature coefficient due to the positive correlation between population and temperature. More specifically, the estimated coefficient for temperature in Table 2 reflects the potentially combined positive impact of population on income per area and the negative effect of temperature on income per area. The positive estimated coefficient might have just reflected the dominant positive impact of population on income per capita. To further explore this possibility, we estimate the extended empirical economic models of (7a) and (7b). The results are presented in Table 3.

Table 3. Temperature-Income Relation when Economic Variables are Included:

Panel A: $\log(\frac{Y_i}{P_i}) = \varphi d_i + a_1 T_i + a_2 T_i^2 + a_3 T_i^3 + b\log(P_i) + e_i$

	T	***T²***	***T³***	***Log(P)***	***Log(S)***	***R²***
Coefficient	-0.02652	-0.00037	0.00004	-0.00049		0.9031
***t*-statistics**	-21.62	-9.77	15.50	-2.59		
***p*-value**	0.0000	0.0000	0.0000	0.0096		

Panel B: $\log(\frac{Y_i}{S_i}) = \tilde{\varphi} d_i + \tilde{a}_1 T_i + \tilde{a}_2 T_i^2 + \tilde{a}_3 T_i^3 + \tilde{b}\log(P_i) + \tilde{c}\log(S_i) + e_i$

	T	***T²***	***T³***	***Log(L)***	***Log(S)***	***R²***
Coefficient	-0.02737	-0.00038	0.00004	0.99787	-1.00992	0.9826
***t*-statistics**	-21.40	-9.89	15.65	450.40	-237.86	
***p*-value**	0.0000	0.0000	0.0000	0.0000		

We estimate the extended empirical economic models of (7a) and (7b).

As soon as we include relevant economic variables such as population and area, the estimated coefficients on temperature become statistically the same for both Equation (7a) and Equation (7b). The estimated coefficient on temperature is equal to -0.02652 (*t* = -21.62) if income is measured by income per capita, and -0.02737 (*t* = -21.40) if income is measured by income per area. This is the central finding of our paper, which suggests that the relationship between temperature and income is *not* dependent on income measurement and is always negative. The implication then is that global warming's impact on income will always be negative, *regardless* of how we measure income. [7]

4.2 Robustness checks

<u>Adding geographic control variables</u>

Following Nordhaus (2006), we add geographic control variables from the G-Econ data set to capture the potential effects of these variables. Our empirical regression models are now

$$\log(\frac{Y_i}{P_i}) = \varphi d_i + a_1 T_i + a_2 T_i^2 + a_3 T_i^3 + b\log(P_i) + \sum_{k=1}^{K} g_k G_{i,k} + e_i \qquad (9a)$$

and

$$\log(\frac{Y_i}{S_i}) = \tilde{\varphi} d_i + \tilde{a}_1 T_i + \tilde{a}_2 T_i^2 + \tilde{a}_3 T_i^3 + \tilde{b}\log(P_i) + \tilde{c}\log(S_i) + \sum_{k=1}^{K} \tilde{g}_k G_{i,k} + e_i \qquad (9b)$$

where $G_{i,k}$ represents geographic variables such as precipitation, minimum, maximum and standard deviation of temperature and precipitation, the cubic polynomial in average temperature and average precipitation, average and standard deviation of altitude, the dummy variables for three different distances from the coast (less than 50 kilometers, at least 50 but less than 100 kilometers and at least 100 but less than 200 kilometers) and 27 dummy variables for 28 soil type (see Nordhaus, 2006 for details).

The results are in Table 4 and are essentially the same as those in Table 3. Again, as long as we include relevant economic variables such as population and area, the estimated coefficients on temperature are statistically the same for both models. The estimated coefficient on temperature is equal to -0.03226 (*t* = -25.72) if income is measured by income per capita, and -0.03236 (*t* = -25.10) if income is measured by income per area. This confirms our findings in Table 2 and suggests that the relationship between temperature and income is not dependent on income measurement and is always negative. The implication again is that global warming's impact on income will always be negative, regardless of how we measure income.

<u>Quantile regressions</u>

From the high R-square values reported in Table 3 and Table 4, it is clear that the included independent variables have done a great job in explaining the variations of the income level measured in both Equation (7a,b) and Equation (9a,b). Nevertheless, there is still unexplained variation across different grid areas even after taking into consideration the variations in economic and geographic factors. The quantile regression technique invented by Koenker and Bassett (1978) is a very useful tool in uncovering any particular pattern in this unexplained variation and in providing a robustness check to the model estimated using the least-squares regressions. Koenker and Hallock (2001) is an excellent primer for quantile regression technique.

[7] Moreover, from the results in the Panel A of Table 3, we can see that the estimated coefficient for population is slightly less than zero (from Panel B its coefficient is slightly less than one), which indicates that the production function exhibits slight decreasing returns to scale and dropping labor can lead to slight bias even when income per capita is used as the dependent variable. This could explain the slight difference between the φ value of -0.02846 for Equation (8a) and -0.02652 for Equation (7a).

Table 4. Temperature-Income Relation when Economic as well as Geographic Variables are Included:

Panel A: $\log(\frac{Y_i}{P_i}) = \varphi d_i + a_1 T_i + a_2 T_i^2 + a_3 T_i^3 + b\log(P_i) + \sum_{k=1}^{K} g_k G_{i,k} + e_i$						
	T	***T²***	***T³***	***Log(P)***	***Log(S)***	***R²***
Coefficient	-0.03226	-0.000684	0.00004	0.00397		0.9066
***t*-statistics**	-25.723	-17.121	17.355	2.038		
***p*-value**	0.0000	0.0000	0.0000	0.041596		
Panel B: $\log(\frac{Y_i}{S_i}) = \tilde{\varphi} d_i + \tilde{a}_1 T_i + \tilde{a}_2 T_i^2 + \tilde{a}_3 T_i^3 + \tilde{b}\log(P_i) + \tilde{c}\log(S_i) + \sum_{k=1}^{K} \tilde{g}_k G_{i,k} + e_i$						
	T	***T²***	***T³***	***Log(P)***	***Log(S)***	***R²***
Coefficient	-0.03236	-0.000684	0.00004	1.004	-1.001	0.9832
***t*-statistics**	-25.096	-17.123	17.015	435.196	-233.872	
***p*-value**	0.0000	0.0000	0.0000	0.0000	0.0000	

Following Nordhaus (2006), we add geographic control variables from the G-Econ data set to capture the potential effects of these variables.

The least squares regression results reported in Table 2 to Table 4 provide estimates of the *average* effects of the various independent variables on the income level. They depict the effects of the independent variables on the dependent variable near the center of the income level distribution. However, the effects of the various economic and geographic variables on income may not be the same across different portions of the income distribution. For example, temperature may impact income differently in grids that have lower income (e.g. most grids in underdeveloped nations such as Belize and Laos with lower quantile in income) than grids that have higher income (e.g. most grids in developed nations such as US and UK with higher quantile in income) even after taking into consideration the effects of the geographic and economic variations. Least-squares regression is incapable of revealing this sort of potential variation when focusing at the center of the income distribution while quantile regression is best for identifying these potential differential impacts. A special case of the quantile regression at the τ = 0.5 quantile (or 50 percentile), the median regression also serves as a robust (to outliers) alternative to the least-squares regression.

Figure 1 presents the regression quantile coefficients of the independent variables (population, temperature and its quadratic and cubic terms) on log GCP per capita used in Equation (7a). Each panel represents the estimated regression quantile coefficients for one independent variable on the dependent variable (log GCP per capita) across the whole spectrum of the dependent variable distribution for $0 \le \tau \le 1$. For example, the vertical axis of the upper right panel in the figure represents the magnitude of the regression quantile coefficients of temperature across the quantiles τ ranging from 0.1 to 0.9 on the horizontal axis. Moving from the left to the right along the horizontal axis, the vertical distances of the dots in the dot-dash line represent the magnitudes of the regression quantile coefficients for τ = 0.1, 0.2, …, 0.8, 0.9 quantiles. The grey band around the dot-dash line in each panel represents the 95% confidence band for the quantile regression coefficients. Hence, the quantile regression coefficient at a particular τ value is considered statistically significantly different from zero when the band at that τ does not cover the horizontal axis. The horizontal solid line represents the magnitude of the least-squares regression coefficient while the dash-lines around it depict the 95% confidence interval for the least-squares coefficient.

Figure 1: Regression quantile coefficients of the temperature-income relation depicted in equation (7a).

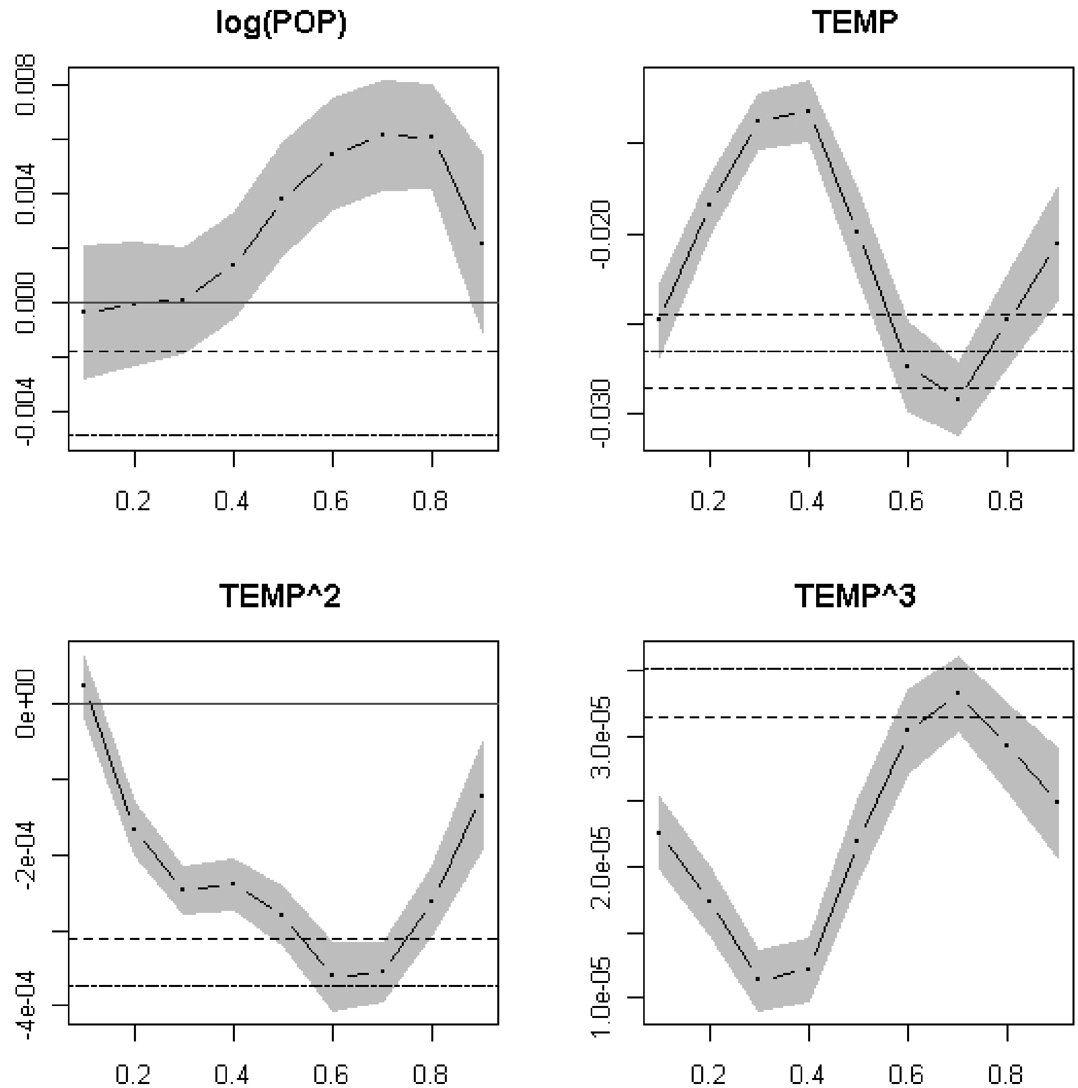

Figure 1 presents the regression quantile coefficients of the independent variables (population, temperature and its quadratic and cubic terms) on log GCP per capita used in Equation (7a). Each panel represents the estimated regression quantile coefficients for one independent variable on the dependent variable (log GCP per capita) across the whole spectrum of the dependent variable distribution for $0 \leq \tau \leq 1$. Moving from the left to the right along the horizontal axis, the vertical distances of the dots in the dot-dash line represent the magnitudes of the regression quantile coefficients for τ = 0.1, 0.2, …, 0.8, 0.9 quantiles. The grey band around the dot-dash line in each panel represents the 95% confidence band for the quantile regression coefficients. The horizontal dot-dash line represents the magnitude of the least-squares regression coefficient while the dash-lines around it depict the 95% confidence interval for the least-squares coefficient.

Figure 2: Regression quantile coefficients of the temperature-income relation depicted in equation (7b).

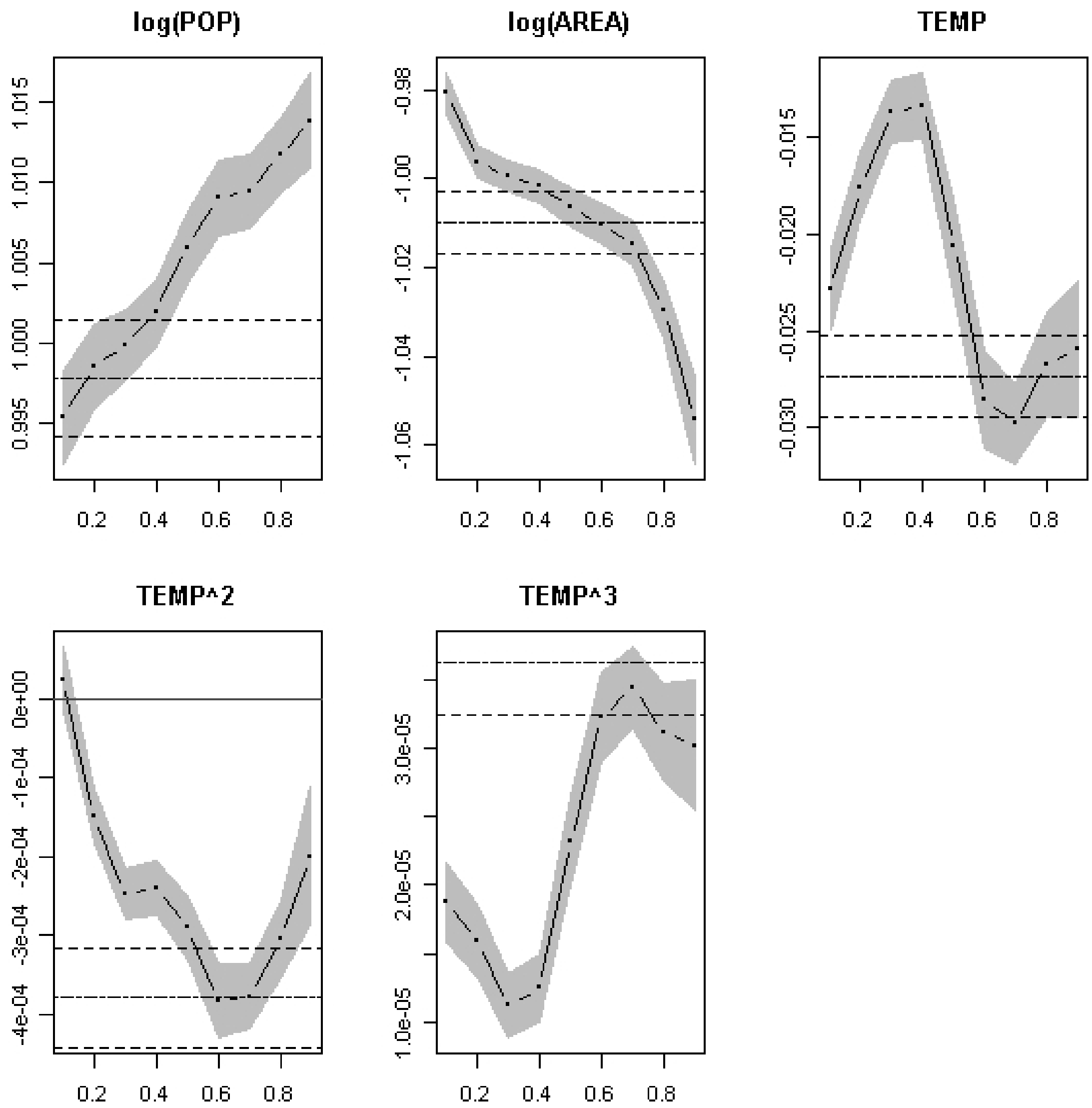

Figure 2 presents the regression quantile coefficients of the independent variables (population, area, temperature and its quadratic and cubic terms) on log GCP per area used in Equation (7b). Each panel represents the estimated regression quantile coefficients for one independent variable on the dependent variable (log GCP per area) across the whole spectrum of the dependent variable distribution for $0 \leq \tau \leq 1$. Moving from the left to the right along the horizontal axis, the vertical distances of the dots in the dot-dash line represent the magnitudes of the regression quantile coefficients for τ = 0.1, 0.2, …, 0.8, 0.9 quantiles. The grey band around the dot-dash line in each panel represents the 95% confidence band for the quantile regression coefficients. The horizontal dot-dash line represents the magnitude of the least-squares regression coefficient while the dash-lines around it depict the 95% confidence interval for the least-squares coefficient.

The regression quantile coefficient for a particular τ measures the impact of a one unit change in the corresponding independent variable on the τ -th quantile of the dependent variable holding constant the effects of all the other independent variables. For example, the quantile regression coefficient of temperature on log GCP per capita is around -0.02 for τ = 0.5 from the upper-right panel of Figure 1. This is close to the -0.0265 estimated by the least-squares regression, and suggests that our results in Table 3 are robust to outliers. As we also can see, across different quantiles, the coefficient of temperature on log GCP per capita is always negative, indicating that the negative relationship between income and temperature is robust across different quantiles. A similar pattern is also observed in Figure 2 when log GCP per area is used in the regression model. Taken together, they suggest that the negative relationship between temperature and income is robust across different quantiles and is not driven by outliers.

Our quantile regression results in Figure 1 and Figure 2 suggest that a one degree Celsius increase in temperature has a more negative impact on grid areas that exhibit higher income than those with lower income.[8] This is different from Dell et al. (2008) who find that the negative relationship only exists in poor countries. What could have explained the difference is an interesting topic for future research. We think this difference may be due to the fact that we use cell-level data while Dell et al. (2008) use country-level data.[9] We think our results are plausible because higher temperature may be associated with more extreme weather events (such as storms, floods, droughts, and heat waves)[10], and Stern (2007) points out that extreme events could lead to significant infrastructure damage and faster capital depreciation which can be particularly costly for developed economies given they have invested a considerable amount in fixed capital each year (a good example is Hurricane Katrina). Nevertheless, the point we try to emphasize here is that the negative relationship between temperature and income is not driven by outliers, and is robust across different quantiles (i.e. not specific to one particular quantile or income level). We will explore the difference between our work and that of Dell et al. (2008) in more detail in future research.

4.3 Implications for global warming

One important application of the negative relationship between temperature and income is to estimate the economic impact of global warming. We focus on the quantile regression results since they provide a more complete picture for a wide spectrum of countries (or grids) ranging from the low-income countries (or low-income grids) such as Nicaragua and Cambodia to the high-income countries (or high-income grids) such as US and UK.

The quantile regression coefficient of temperature on log GCP per capita is around -0.03 for τ = 0.7 from the upper-right panel of Figure 1. This implies that the estimated impact of a one degree Celsius increase in temperature is an approximately 3% decrease in GCP per capita for the grid areas that are at the upper 0.3 quantile (or upper 30 percentile) of the income distribution. However, the estimated impact of the same one degree Celsius increase in temperature on the grid areas that are at the lower 0.3 quantile is a roughly 1.5% decrease in GCP per capita.

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[8] For instance, the quantile regression coefficient at τ = 0.3 and 0.7 is roughly -0.014 and -0.029, respectively in Figure 1. That tells us that a one degree Celsius rise in temperature will have an effect of reducing GCP per capita by 1.4% for the grid areas that are at the lower 0.3 quantile (or lower 30 percentile) of the GCP per capita distribution while the same one degree Celsius increase in temperature will have a larger negative impact of reducing GCP per capita by 2.9% for the GCP per capita distribution. Hence, the same one degree Celsius increase in temperature has a higher negative impact on higher productive grid areas than the lower productive grid areas.

[9] As Nordhaus (2006) points out, using cell-level data rather than country-level data may make temperature measurement more meaningful.

[10] IPCC (2007) points out that gradual global warming can increase the intensity and frequency of extreme events.

The IPCC's best estimate for global average surface warming at the end of the 21st century ranges from 1.8°C (with 66 percent confidence interval from 1.1°C to 2.9°C) to 4.0°C (with 66 percent confidence interval from 2.4°C to 6.4°C). The most commonly used benchmark is a 3.0 degrees Celsius increase in temperature (e.g. Nordhaus, 2006). Thus the economic impact on income due to global warming based on our parameter estimates is an about 9% decrease in income for the high-income grid areas and a roughly 4.5% decrease in income for the lower-income grid areas. Our results, therefore, confirm previous studies and suggest that the climate mitigation policy should be more aggressive.

5. Conclusion

The relationship between temperature and income is important because it enables economists to estimate the economic impact of global warming without assuming a structural model. Until recently, empirical evidence generally suggests that there is a negative relationship between temperature and income, and therefore global warming has adverse impact on economic activity. However, recently Nordhaus (2006) finds that the temperature-income relationship depends on how researchers measure income. If income is measured by income per capita (the typical measurement used in the literature), the relationship is negative; however, if income is measured by income per area (income/km^2), the relation is positive. His findings, therefore, suggest that the impact of global warming may be positive if we focus on income per area as the income measurement.

We show in this paper that the results of Nordhaus (2006) may be due to a model misspecification or an omitted-variable problem. Based on a temperature-income model that is well motivated by theory, we find that the relationship between temperature and income is *not* dependent on income measurement, and it is always negative. Our results are robust regardless of whether we include geographic variables as in Nordhaus (2006), or whether we use the least-squares regression or quantile regression. Implied from our quantile regression results, the adverse impact of a 3.0 C increase in temperature (due to global warming) can be as much as a 9% decrease in income for developed nations such as the United States and the United Kingdom. The impact is significant and may call for a more aggressive climate mitigation policy.

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