Climate change and economic growth in sub-Saharan Africa: A nonparametric evidence

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Abstract

Climate change has been classed as the greatest and urgent global issue facing humanity today, yet the empirics of the debate remain largely muted, more so with reference to sub-Saharan Africa (SSA), where the impact of warming global temperatures are forecasted to have the worst impact. This paper is a contribution to the empirics of climate change and its effect on sustainable economic growth in SSA using nonparametric regression techniques. We establish the following: the relationship between real GDP per capita on one hand and climate change on the other hand, is intrinsically linear and monotonically decreasing at a constant proportionate rate. This relationship holds for both temperature and precipitation.

Keywords: Climate change, sub-Saharan Africa, Sustainable Growth, Nonparametric techniques.

JEL Classification: C14; C23; O11; O13; O40; Q54

1 Introduction

An issue that has received a great deal of attention among environmentalists is the interaction between the climate and the economy. A popular position is that climate change will eventually bring growth to a halt and accelerate poverty in a world with growing population. Climate change is expected to reduce the productivity of production factors, particularly those employed in agriculture and related activities. The proponents of this channel of transmission predict that developing countries will bear the lion's share of the adverse impact of climate change due to their dependence on climate sensitive sectors. Another potential source of drag on growth from climate change is the diversion of resources from

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productive investments to mitigation and adaptation investments. Again meeting the burden of mitigation and adaptation investment represents a greater policy challenge to the developing world due to their low saving and investment rate. Balancing this with the quest for higher growth in this part of the world as an effort to reduce the incidence of poverty makes the choice of mitigation and adaptation investment a hard one.

Unsurprisingly, the issue of the potential impact of climate change on long run economic growth has attracted the attention of researchers in the field of environmental and energy economics. A growing number of theoretical and empirical studies have examined the possible impacts of climate change on economic growth (see for instance: Frankhauser and Tol, 2005; Milliner and Dietz, 2011; Acemoglu, et al, 2012; Nordhaus, 2005; Dell et al, 2008; 2009; Odusola and Abidoye, 2012; Jones and Oklen, 2010; Lanzafame, 2012; Alagidede, et al 2014). However, the evidence reported in the empirical literature is so far less than conclusive.

There is a prevalent view that the relationship between economic growth and climate change is nonlinear. Previous empirical studies have taken this concern into account by incorporating quadratic terms of the climate variables (temperature and precipitation) into their models in consonance with the Ricardian view (see for instance: Alagidede, et al, 2014; Lanzamfame, 2012; Odusola and Abidoye, 2012; Jones and Oklen, 2010 and Dell et al, 2009; 2008). This paper questions the form of functional specifications that exist in the extant literature on climate change and economic growth. While the argument of possible nonlinearities between growth and climate change is a logical one, the exact form of this nonlinear relationship is unknown, *ex ante*. Thus, incorporation of quadratic terms may not adequately capture the true nonlinear relationship between climate change and economic growth. This paper proposes nonparametric kernel regression methods to estimate the "true" relationship between climate change and economic growth for our selected sample of SSA countries.

Briefly, we show that the relationship between real GDP per capita on one hand and climate change (with annual variations in mean annual temperature and precipitation as proxy) on the other hand, is intrinsically linear and monotonically decreasing at a constant proportionate rate. This finding sharply contradicts the Recardian view of climate impact on economic performance which suggests a quadratic relationship between income and climate change. This could probably mean that temperature in most of the countries in sub-Saharan Africa is already higher than the threshold level at which the effect of temperature changes on income per capita turns negative. The implication of the negative relationship between income per capita and mean annual temperature is that climate change can impose a heavy burden on poverty reduction efforts in the sub-Saharan Africa, which unfortunately is already the poorest among the developing world. It is, however, surprising that the relationship between income and precipitation is negative. Given the dominance of agriculture in GDP and employment in most SSA countries, and the fact that agriculture in sub-Saharan Africa is mostly rain fed, increases in annual mean rainfall is expected to raise per capita income. Nevertheless, the negative effect of precipitation on per capita income is not totally unreasonable, taken into account flood cases and destructive effects of tropical rains on farms, apartments and public infrastructure, in general. The log-linear relationship reported here does not support the quadratic parametric specification popular in the extant literature.

Section 2 provides information on data sources, model specification and short description of the nonparametric modelling technique. Section 3 presents the results of our estimations. Section 4 concludes the paper.

2 Data and Empirical Strategy

2.1 Data

This empirical study relies on the same panel dataset as Alagidede, et al (2014). The data was collected from different data sources from 1960 to 2009 for 27 sub-Saharan African countries[1]. The criterion used in the selection of the candidate countries was based on the availability of data, particularly on the proxies used for climate. Furthermore, data on real GDP per capita and other macroeconomic variables are gleaned from *World Development Indicators* and *African Development Indicators* databases of the World Bank. The Climate data on temperature and precipitation at the country level were taken from the Climate database of the Food and Agricultural Organisation of the United Nations.

2.2 Nonparametric Technique

In order to estimate the growth effect of climate change for a sample of sub-Saharan African countries, we follow Alagidede, *et. al.* (2014) and specify the growth equation generally as:

$$\ln y_{it} = f(Z_{it}, \ln TEMP_{it}, \ln PREC_{it}) + \varepsilon_{it}, \qquad (1)$$

where i is a country index, t is time index, y represents real GDP per capita; $Z$is a vector of control variables consisting of the gross domestic capital formation as a ratio to GDP (a proxy measure for the investment rate), trade openness, official development assistance as a ratio to GDP, and domestic credit to the private sector as a ratio of GDP; $TEMP$ is temperature in degree Celsius; and $PREC$is precipitation. We also control for country and time indexes (both being discrete) in the nonparametric model to be described shortly.

We estimate equation (1) using the local linear kernel estimator.[2] The local linear estimator possesses the following advantages over other popular kernel methods such as the local constant estimator. The traditional local constant kernel estimator is known to suffer from boundary bias, while the local linear estimator is known to be among the best boundary-correction methods so far. As

[1] Benin, Burkina Faso, Cape Verde, Cote d'Ivoire, Ghana, Guinea, Sierra Leone, Senegal, Togo, Mali, Niger, Nigeria, Liberia, South Africa , Congo DR, Zambia, Sudan, Zimbabwe, Madagascar, Mozambique, Mauritius, Malawi, Mauritania, Cameroun, Ethiopia, Kenya and Lesotho.

[2] See Li and Racine, (2004; 2007) for detailed description of the local linear estimator.

noted by Li and Racine (2004, 2007), when the underlying relationship is somewhat linear, the local linear nonparametric estimator can have a convergence rate that is arbitrarily close to the parametric rate. However, this estimator takes into account all possible nonlinearities and interactions among the variables in our model that the parametric model may not capture. This makes the local linear estimator superior to a fully parametric estimator, even if the underlying relationship is somewhat linear.

Estimating the above model is not without challenge. A crucial challenge is that, the exact mathematical form of the model in equation (1) is unknown, *a priori*. In particular, the relationship between income and the climatic factors (temperature and precipitation) is assumed to be quadratic, according to the Racardian view. Previous researchers have accounted for this potential nonlinearity in economic growth and climate change by including up to a second order polynomial terms for temperature and precipitation in the above equation, while assuming that the relationship between economic growth and the remaining determinants are linear. However, such an approach is not without problems. For instance, while the argument of nonlinearity is sound, there is no assurance that the relationship is quadratic as the previous empirical literature assumes. More so, even if we are certain about the nature of the functional form of the relationship between economic growth and climatic indicators, the possibility of nonlinear relationship between economic growth on the one hand and the remaining regressors on the other hand cannot be ruled out, *a priori*.

Taken the above into account, the empirical analysis in this paper tests the null hypothesis that the popular parametric models in this strand of the literature are correctly specified. When such evidence is found wanting, we proceed to estimate the above growth model using fully nonparametric kernel regression methods. This approach is a two-step procedure, where on the one hand we must estimate the optimal bandwidth parameter to be used for kernel smoothing, while on the other hand the estimated bandwidth are used to estimate the nonparametric regressions relationships. In order to visualize the estimated relationships and their marginal effects, the partial regression relationships and partial gradients are also plotted. We describe these steps in turn.

2.3 A Consistent Test for Correct Parametric Specification

Prior to running our proposed fully nonparametric model, we evaluate the popular parametric specifications using a consistent test for correct parametric specification. Our objective here is to test the null hypothesis that a parametric model is correctly specified. This hypothesis is stated here as

$$H_0 : \quad P[E(Y_{it}|X_{it}) = m(X_{it}, \alpha)] = 1 \quad , \tag{2}$$

where $m(\cdot)$ is a known function (the assumed parametric regression model) with α being $q \times 1$ vector of unknown parameters. The null hypothesis in equation

(2) is tested against the following alternative given by equation (3).

$$H_1: \quad P[E(Y_{it}|X_{it}) = m(X_{it}, \alpha)] < 1 \tag{3}$$

To test this hypothesis, we employ a test statistic that is based on a consequence of correct specification which requires that the residuals satisfy $E[E(\varepsilon_{it}|X_{it})^2] = 0$ if and only if the model is correctly specified. We consistently estimate $E(\varepsilon_{it}|X_{it})$ using nonparametric methods. Note that by the law of iterated expectations, $E[\varepsilon_{it}E(\varepsilon_{it}|X_{it})]$. We adopt a density weighted version for testing purposes given by $J = E[\varepsilon_{it}E(\varepsilon_{it}|X_{it})f(X_{it})$, where $\varepsilon_{it} = Y_{it} - m(X_{it}, \alpha)$ and $f(X_{it})$ is a joint probability density function (PDF). The purpose of using density weighting is to avoid the presence of a random denominator. Note that $J = E[E(\varepsilon_{it}|X_{it})]^2 f(X_{it})] \geq 0$ and $J = 0$ if and only if the null hypothesis in equation (2) is true. Therefore, J serves as a valid candidate for testing the null hypothesis against the alternative. The sample test statistic is calculated as

$$J_{(N\times T)} = \frac{1}{N}\sum_{i=1}^{n}\sum_{t=1}^{T}\hat{\varepsilon}_{it}\hat{E}_{-it}(\varepsilon_{it}|X_{it})\hat{f}_{-it}(X_{it}) \tag{4}$$

where $\hat{\varepsilon}_{it} = Y_{it} - m(X_{it}, \hat{\alpha})$ is the residual obtained using the parametric null model, $\hat{\alpha}$ is $\sqrt{N}$-consistent estimator of α under the null hypothesis of correct specification and $\hat{E}_{-it}(\varepsilon_{it}|X_{it})\hat{f}_{-it}(X_{it})$ is a leave-one-out kernel estimator of $E(Y_{it}|X_{it})f(X_{it})$. A wild-bootstrap is used to obtain the test statistic for the null distribution.

2.4 Cross-Validated Local Linear Nonparametric Estimator

Conditional on the failure to accept the null hypothesis of correct specification of the parametric model, we proceed by estimating the model using fully nonparametric regression methods. Nonparametric methods are robust to functional specification issues since they allow the data to determine the appropriate model. Nonparametric methods are consistent under fairly weak set of assumptions and are best suited to situations involving large data sets. The application of nonparametric methods is not without cost, however, as nonparametric methods are computationally intensive and are slower to converge.

To describe the nonparametric model for our general specification in (1), we rewrite the model as

$$Y_{it} = g(x_{it}^c, x_{it}^d) + \varepsilon_{it}, \quad i = 1, ..., N; \; t = 1, ..., T \tag{5}$$

where $x_{it}^c \in R^q$is a set of continuous (a subset of X_{it}) regressors of dimension q and $x_{it}^d \in \mathrm{S} \times \mathrm{S} \times ...\mathrm{S}$ is a set of discrete (a subset of X_{it}) regressors of dimension r. The unknown conditional expectation $g(\cdot)$ and its derivatives are not observable but are consistently estimated using nonparametric methods. Define the derivative of

$g(x_{it}^c, x_{it}^d) : \beta(x^c) \underline{\underline{def}}\, \nabla g(x^c, x^d) \equiv \partial g(x^c, x^d)/\partial x^c$ where $\nabla g(\cdot)$ is a $q \times 1$ vector. Define$\delta(x^c, x^d) = \left(g(x^c, x^d), \beta(x^c)'\right)'$. $\delta(x^c, x^d)$ is a $(q+1) \times 1$ vector-valued function whose first component is $g(x^c, x^d)$ and whose remaining q components are the first derivatives of $g(x^c, x^d)$ with respect to x^c. Taking a Taylor series expansion of $g(x^c, x^d)$ at x_j^c, we obtain $g(x_{it}^c, x_{it}^d) = g(x_{jt}^c, x_{it}^d) + (x_{it}^c - x_{jt}^c)\beta(x_{jt}^c) + R_{ijt}$, where

$R_{ijt} = g(x_{it}^c, x_{it}^d) - g(x_{jt}^c, x_{it}^d) - (x_{it}^c - x_{jt}^c)'\beta(x_{jt}^c)$. We therefore rewrite equation (5) as

$$\begin{aligned} Y_{it} &= g(x_{jt}^c, x_{it}^d) + (x_{it}^c - x_{jt}^c)'\nabla g(x_{jt}^c, x_{it}^d) + R_{ijt} + \varepsilon_{it} \\ &= \left(1, (x_{it}^c - x_{jt}^c)'\right) \delta g(x_{jt}^c, x_{it}^d) + R_{ijt} + \varepsilon_{it} \end{aligned} \tag{6}$$

We estimate equation (6) using the local linear kernel estimator.[3]

Kernel methods require selecting bandwidths. Here we use least-squares cross-validation to select the bandwidth vector (h, λ). The estimation of the optimal bandwidth is similar to minimizing the sum of squared residuals for a parametric regression model. However, we use a leave-one-out estimator in the cross-validation function to avoid over fitting. A leave-one-out local linear kernel estimator of $\delta(x_{it}^c, x_{it}^d)$ is obtained by a kernel weighted regression of Y_{it} on $\left(1, (x_{it}^c - x_{jt}^c)'\right)$ and x_{it}^d.

The leave-one-out kernel estimator is given by

$$g_{-i}(x_{it}^c, x_{it}^d) = e_1' \hat{\delta}_{-i}(x_{it}^c, x_{it}^d) \quad , \tag{7}$$

where e_1 is a $(q+1) \times 1$ vector, whose first element is one with all the remaining being zero. We choose (h, λ) to minimize the least-squares cross-validation function given by

$$CV(h, \lambda) = \sum_{i=1}^{N} \sum_{t=1}^{T} \left[Y_{it} - \hat{g}_{-i}(x_{it}^c, x_{it}^d)\right]^2, \tag{8}$$

where $\hat{g}_{-i}(x_{it}^c, x_{it}^d)$is defined in equation (7). The resulting bandwidth vector is denoted $(\hat{h}, \hat{\lambda})$.

Having obtained the appropriate bandwidth vector, we then estimate $\delta(x_{it}^c, x_{it}^d)$ by

$$\begin{aligned} \hat{\delta}(x_{it}^c, x_{it}^d) &= \begin{pmatrix} \hat{g}(x_{it}^c, x_{it}^d) \\ \hat{\beta}(x_{jt}^c) \end{pmatrix} \\ &= \left[\sum_{i=1}^{N} W_{\hat{h}ix} \begin{pmatrix} 1 & (x_i^c - x_j^c)' \\ x_i^c - x_j^c & (x_i^c - x_j^c)(x_i^c - x_j^c)' \end{pmatrix} L_{\lambda ij}\left(x_i^d, x_j^d, \lambda\right)\right]^{-1} \\ &\times \sum_{j=i} W_{\hat{h}ix} \begin{pmatrix} 1 \\ x_i^c - x_j^c \end{pmatrix} L_{\lambda ij}\left(x_i^d, x_j^d, \lambda\right) Y_{it} \end{aligned} \tag{9}$$

where $W_{\hat{h}ix}$ is a product kernel for continuous data such as a product of univariate Gaussian kernels and $L_{\lambda ij}$ is a product kernel for discrete data.

[3] See Li and Racine, (2004; 2007) for detailed description of the local linear estimator.

As a final step we plot the partial regression and partial gradient or partial response surfaces that measure how the dependent variable (log of GDP per capita) and its response surface change in response to changes in one of the regressors, holding all other variables constant at their medians or modes. Thus a partial regression and partial gradient that measure how the outcome variable and its response surface change in response to changes in a covariate when all other covariates are held constant at their respective medians/modes is plotted for each of the covariates. All the figures are plotted within 95% confidence band by bootstrapping.

3 Results of the Nonparametric Estimations

This section of the paper reports and discusses the results of the estimated relationship between the log of real GDP per capita and temperature and precipitation (both on log scale) using nonparametric regression technique described in Section 2 of the present paper. The results of the consistent model specification tests for correct parametric specification are reported in Table 1. The results of the nonparametric regression estimates are reported in Table 2 and Figures 1 and 2.

In both cases the null hypothesis of correct parametric specification is flatly rejected at the 1% error level. On the basis of this result, we proceed to estimate the model using the more flexible fully nonparametric regression methods, which does not require us to assume any specific functional form for the model specified in equation (1). Table 2 reports the summary statistics of the nonparametric regression estimates whiles Figures 1 and 2 show the plots of partial regression and partial response (marginal response rate or partial elasticity surfaces) respectively.

As was indicated in the methodology section of the paper, the nonparametric estimation begins with estimation of the optimal bandwidths and the corresponding scale factors for each of the independent variables. A lower value of the bandwidth and scale factor for a particular covariate implies that the underlying relationship between real GDP per capita and the variable in question are nonlinearly related. On the other hand, if the estimated bandwidth and scale factor are large and approaching infinity, then the relationship is linear and the local linear kernel estimator converges to the parametric estimator on the coefficient on that variable. On a whole, the estimated bandwidths are very large for temperature, precipitation, trade openness, and gross domestic capital formation expressed as a ratio of GDP (a proxy for the investment rate). However, the estimated bandwidths for domestic credit to the private sector to GDP ratio (DCP) and official development assistance to GDP ratio (ODA) as well as the two categorical variables (country index and time index) are quite smaller, approaching zero than to infinity. The significant divergence of the optimal bandwidths for TEMP, PREC, TRADE and GCF from zero towards infinity implies that the relationship between the dependent variable (real GDP per capita) on the one hand and these regressors on the other hand, is somewhat linear. This linearity in the underlying relationship between GDP per capita and that of TEMP, PREC, TRADE and GCF is more transparent from Figures 1 and 2. This implies that a parametric model that imposes linear structure prior to estimation could lead to bias estimation and wrong inference. Reasoning similarly, the estimated bandwidths and the scale factors for DCP and ODA suggest that the underlying relationship between real GDP per capita on the one hand and DCP and ODA on the other hand are nonlinear. The nonlinear relationship between real GDP per capita and ODA and DCP becomes more transparent from the plots of partial regression relationship and the partial response surfaces in Figures 1 and 2 respectively.

The results of the kernel regression estimations are presented alongside the bandwidth estimates in Table 2. The R-squared and residual standard errors indicate a good fit for the estimated nonparametric regression. The estimated R-squared is 0.994454 while the residual standard error is only 0.0437545. Thus, approximately 99.45% of the observed variation in real GDP per capita in sub-Sahara Africa is accounted for by the regressors in our model. The rather high R-squared value coupled with the relatively low residual standard error for the nonparametric regressions are good indication that our model really fits the data well. The estimated relationships are presented as plots of partial regression relationships (Figure 1) and partial gradients (Figure 2).

We now consider the 'partial regression' and 'partial gradient' or partial response surfaces that measure how the dependent variable (*the log of real GDP per capita*) and its response surface change in response to changes in an explanatory variable, holding all other variables constant at their medians/modes. All figures contain 95% variability asymptotic bands. The estimates of the local-linear kernel estimator for the growth model are presented in Figures 1 and 2 above.

The plots in Figures 1 and 2 reveal that the relationship between *the log of real GDP per capita* and the two climate variables, temperature (log(TEMP)) and precipitation (log(PREC)), is linear. As Figure 1 shows, the relationship between real per capita GDP and the log of mean annual temperature for a panel of sub-Saharan African countries is monotonically decreasing which contradicts the inverted U-shape path relationship suggested in the Ricardian view on the climate change impact on economic performance. This could probably mean that temperature in most of the countries in sub-Saharan Africa is already higher than the threshold level at which the effect of temperature changes on income per capita turned negative. The implication of the negative relationship between income per capita and mean annual temperature is that climate change can impose a heavy burden on poverty reduction efforts in the sub-Saharan Africa, which unfortunately is already the poorest among the developing world.

From the plot of partial regression relationship in Figure 1 and the plot of partial gradients in Figure 2, the relationship between the logarithm of real GDP per capita and logarithm of precipitation is linear and monotonically decreasing. It is however surprising that the relationship between income and precipitation is negative. Given the dominance of agriculture in GDP and employment in most SSA countries, and the fact that agriculture in sub-Saharan Africa is mostly rain fed, increases in annual mean rainfall is expected to raise per capita income. However, the negative effect of precipitation on per capita income is not totally unreasonable, taken into account flood cases and destructive effects of tropical rains on farms, apartments and public infrastructure, in general. This log-linear relationship reported here does not support the quadratic parametric specification popular in the extant literature.

Consistent with the linear relationship between the log of real GDP per capita and the mean of annual temperature, Figure 2 shows that the response rate of real GDP per capita does not vary within the domain of mean temperature, measured on a log scale. Again, this fact cast doubt on the estimated parameters on parametric models with quadratic specification of the temperature term in the growth and income equations. It is not surprising that our consistent model specification test flatly rejected the quadratic specification. Again, from Figure 2, the response rate of real GDP per capita does not vary within the domain of precipitation, measured on a log scale.

As evident from Figures 1 and 2, the relationship between trade openness and per capita income for a panel of selected SSA countries is linear and monotonically increasing. The implication here is that, income per capita is high in countries with a large trade share in GDP compared to similar countries but with lower trade shares in GDP. As can be seen from Figure 2, the response rate of real GDP per capita does not vary within the domain of trade openness, measured as total trade to GDP ratio.

Also, Figures 1 and 2 revealed that the relationship between gross capital formation as a ratio of GDP (GCF), a proxy for the investment rate, and real GDP per capita is linear and monotonically increasing. This means that per capita income is higher in countries with high rate of investment compared with similar countries, but with lower rate of investment. This evidence is consistent with the predictions of neoclassical growth theory and the empirical tests of the theory, which assign an important role to the rate of capital accumulation in accounting for differential growth rates across time and space and consequently cross-country income differences. Again, from Figure 2, the response rate of real GDP per capita does not vary within the domain of gross capital formation expressed as a ratio of GDP.

Interestingly, the relationship between real GDP per capita and domestic credit to the private sector as a ratio of GDP is positive and nonlinear as seen from Figures 1 and 2. The plots of the partial regression relationship and the corresponding partial gradient suggest that the log of income per capita increases at an increasing rate in domestic credit to the private sector. This implies that there is convex relationship between income and private sector credit. As revealed by Figure 2, the response rate of real GDP per capita varies within the domain of domestic credit to private sector to GDP ratio.

Clearly, official development assistance to GDP ratio (ODAY) has negative relationship with per capita income. However, the relationship is nonlinear. As the plot of partial gradient between these two variables shows [see Figure 2], the magnitude of the negative impact of aid on growth reduces with increasing aid inflows. This implies that, above some threshold, effect of aid on growth could turn positive and significant.

4 Conclusion

This paper is a contribution to the empirics of climate change and economic growth in sub-Saharan Africa. Although substantial amount of academic research has been devoted to climate change the overall effects on long run growth is not conclusive, both in terms of the exact functional relationship (which casts serious doubts on parametric estimates, which assumes that the specific mathematical relationship is known prior to estimation) and the direction of the effect if any at all. Moreover, the evidence pertaining to sub-Saharan Africa is largely anecdotal and mainly confined to what research elsewhere has to say by extrapolation. An empirical appraisal of this topical issue is thus of concern to inform the direction of policy, and to position SSA properly in efforts aimed at mitigating the effects of global warming. In this paper, we estimate the effect of climate change on economic growth on a subset of SSA countries using nonparametric regression method. The novelty of this work rests on the nonparametric method, thereby accounting for almost all the nuances that are left out in extant studies.

Our results indicate that the relationship between real GDP per capita on one hand and climate change (with mean annual variations temperature and precipitation as a proxy) is intrinsically linear and negative. This suggests that increases in temperature are harmful to growth performance in the long-run, all things being equal. Given that SSA relies heavily on the agricultural sector for the bulk of economic output, we surmise that higher temperatures could actually reduce agricultural output with ramifications for industrial growth, job creation and poverty reduction efforts.

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Table 1: Consistent Test for Correct Parametric Specification

Parametric Specification	J-Statistic	p-value
$\log(RGPPC) = \alpha_0 + \alpha_1 \log(TEMP) + \alpha_2 \log(PREC) + \alpha_3 TRADE + \alpha_4 GCF + \alpha_5 DCP + \alpha_6 ODA + \varepsilon$	10.07878	<2.22e-16***
$\log(RGPPC) = \delta_0 + \delta_1 TEMP + \delta_2 TEMP^2 + \delta_3 PREC + \delta_4 PREC^2 + \delta_5 TRADE + \delta_6 GCF + \delta_7 DCP + \delta_8 ODA + \varepsilon$	9.974742	<2.22e-16***

Table 2: Estimated Local-Linear Nonparametric Regression

Bandwidth Selection Method: Expected Kullback-Leibler Cross-Validation

Regression Type: Local-Linear | Bandwidth Type: Fixed

Formula: log(RGPPC) = log(TEMP) + log(PREC) + TRADE + GCF + DCP + ODA + Ordered(YEAR) + Factor(ID)

Regressor	Bandwidth	Scale Factor
log(TEMP)	726476.8	10467908
log(PREC)	2525208	9254119
TRADEY	1149855	8964530
GCFY	356091.7	10505283
DCPY	0.5242165	8.89504
ODAY	0.2775705	7.832747
Ordered(YEAR)	0.8052298	Lambda Max: 1
Factor(ID)	0.001349056	Lambda Max: 1
Residual Standard Error: 0.0437545		R-Squared: 0.994454

Notes: Number of observation is 697. Objective Function Value: -3.888143 (achieved on multistart 2). Continuous Kernel Type: Second-Order Gaussian. Unordered Categorical Kernel Type: Li and Racine . Number of Unordered Categorical Explanatory Variables: 1. Ordered Categorical Kernel Type: Li and Racine . Number of Ordered Categorical Explanatory Vars: 1

Figure 1: Partial Regression Relationships

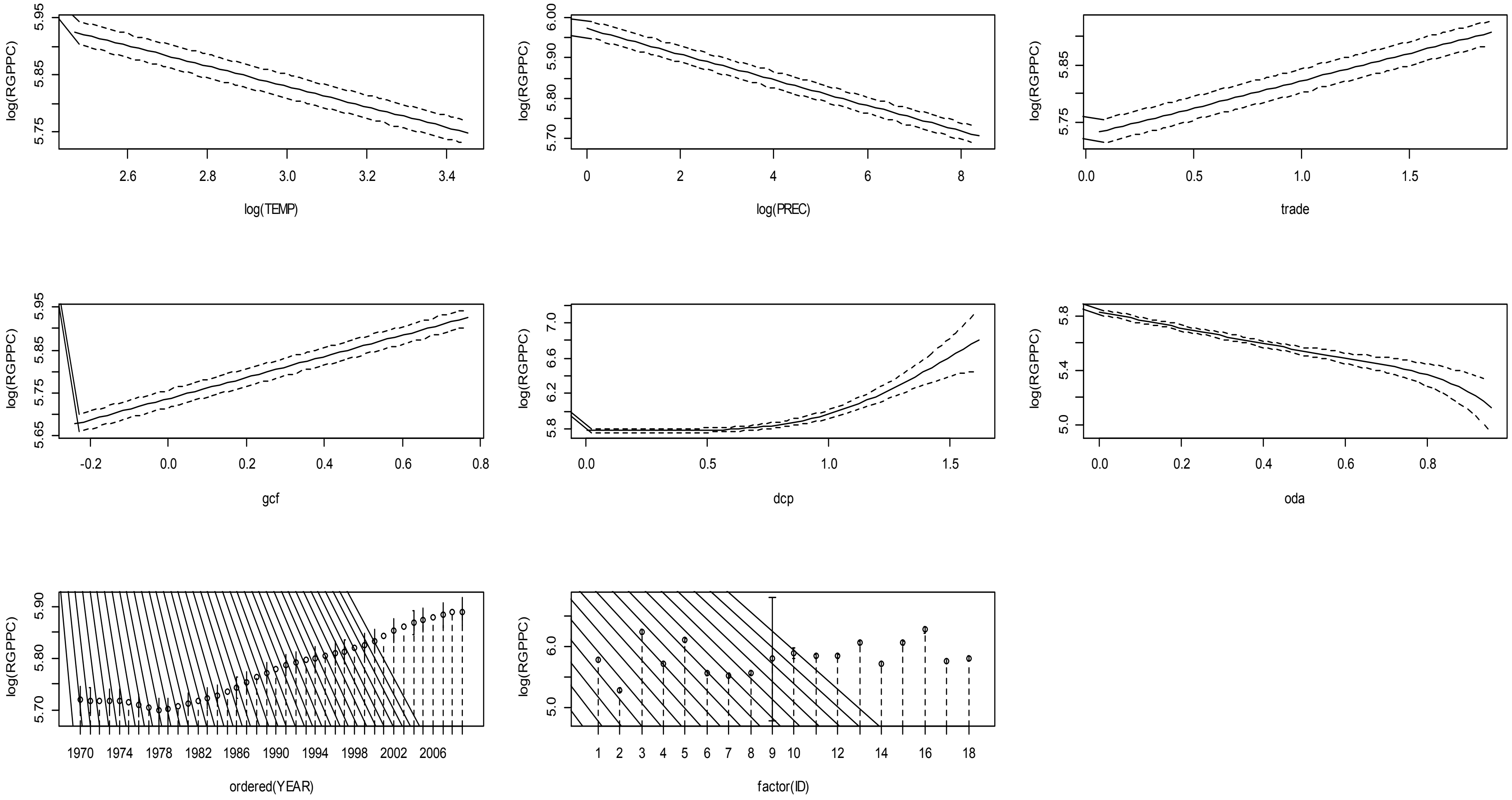
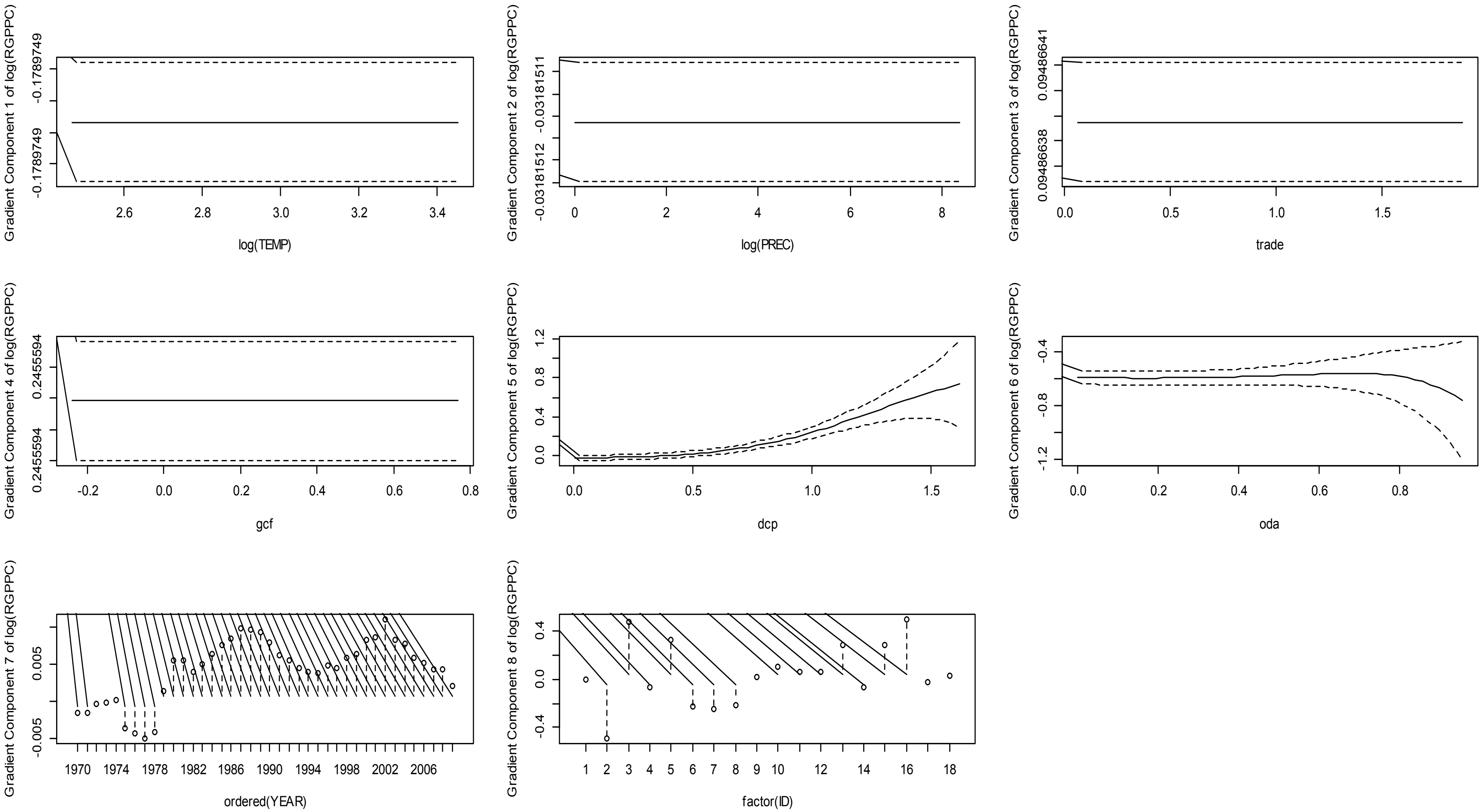


Figure 2: Plots of Partial Regression Gradients/Slopes



AII: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
RGDPPC	720	533.55	679.68	82.7	3796
TEMP	720	24.88	4.13	11.8	31.6
PREC	720	475.92	287.25	1	4433
GCFY	720	19.07	9.32	1.6	76.7
TRADEY	720	61.77	30.36	6.3	187.7
DCPY	720	20.95	22.10	0.7	162
ODAY	720	9.30	7.97	0	95.5