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AID AND ECONOMIC GROWTH: A ROBUST APPROACH

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ABSTRACT. This paper uses panel data and the Local Linear Kernel Estimator (LLKE) to investigate the effects of aid on economic growth in developing countries. Specifically, we investigate the robustness of a popular parametric specification of the aid/economic growth relationship in Less Developed countries (LDCs). First, we find that aid has a significant impact on economic growth given the support of the sample data we use. However, the effect depends on how aid is measured. We find a positive growth effect when aid is measured as *aidgni* but no significant growth effect when aid is measured as *aidpercap*. Second, we find some evidence of increasing returns to *aidgni*. Finally, we find that a “good” policy environment increases the effectiveness of aid in LDCs, all things equal. The impact of the policy environment on growth varies according to how the policy environment is measured. Our results generally support the popular quadratic parametric specification of the aid/growth relationship. Our results have implications for aid policy and for research on the effectiveness of aid.

1. INTRODUCTION

This paper uses a robust nonparametric local linear kernel estimator (LLKE) that admits categorical and continuous data, panel data from a large sample of Less Developed Countries (LDCs), five measures of policy, and two measures of aid to investigate the robustness and appropriateness of a popular parametric specification of aid/economic growth relationship in LDCs. The LLKE takes into account all possible non-linearities and interactions among the variables in the aid/growth equation that common parametric specifications fail to account for. Nonparametric methods can also provide a consistent test for the appropriateness of a

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parametric specification, hence are particularly well suited to testing robustness of the popular parametric relationship between aid and economic growth. We use the LLKE estimator to estimate a growth equation that accounts for the traditional growth variables, aid inflows, as well as governance variables.

To fulfill the millennium development goals (MDGs), developed countries have pledged to substantially increase aid to developing countries. For example, the UNPD's 2006, *Doubling Aid: Making the 'Big Push' Work* envisions doubling aid to Africa in the coming decade. Similarly, the *The Commission for Africa Report* (2006) advocates substantially increasing aid to Africa. Indeed, the volume of aid to LDCs has started trending upwards after declining in the 1990s.¹ This increase in aid volume is occurring at a time when there is a disagreement on the effectiveness of aid in LDCs. Worse, there is no agreement on the robustness or the functional form of any relationship between aid and growth in LDCs. Given the objective of using aid to spur growth and reduce poverty, the increase in aid, and the lack of agreement on the relationship between aid and growth in LDCs, it is important to establish the robustness of the relationship between aid and economic growth. This paper contributes to the literature in this regard.

Research on aid effectiveness in LDCs has produced contradictory result, at best. While some studies find aid to have a positive growth impact, others find no growth impact; still others find that aid has a positive growth effect only if it is conditioned on "good policies". Some researchers even find a negative growth effect. The inconclusive evidence on the aid/growth relationship itself cries out for robustness checks to guide further research and policy on the subject. This paper contributes to the literature in this regard.

A popular approach to the study of aid/growth relationship is to specify a parametric growth equation in which aid enters in a quadratic form as well as its interaction with policy. Aid enters in a quadratic form on account of an assumed diminishing returns to aid while aid/policy interaction term accounts for conditional growth effect hypothesis. A positive and significant coefficient on aid combined with a negative and significant coefficient on the

square of aid indicates diminishing returns to aid while a positive and significant coefficient on the aid/policy interaction term is indicative of conditional growth effect of aid. This specification also include other growth regressors, such as physical and human capital, as control variables. Most of recent studies of the aid/growth relationship use panel data and a dynamic panel estimator or some form of instrumental variables (IV) estimator to draw their conclusion. These studies therefore follow the popular parametric specification we have sketched above. Our paper focuses on testing the appropriateness of this specification of the aid/growth relationship.

This paper makes three contributions to the aid/growth literature. First, this is the only paper we are aware of that uses the LLKE to investigate the robustness of the aid/growth relationship and to test the appropriateness of the relationship. As Rajan and Subraminian (2005) argue, the results from parametric GMM estimators, the estimators of choice in recent aid/growth research, depend on the structure imposed by the functional forms and instrument sets chosen by the researcher. Because the LLKE does not impose parametric structure, it is better able to model the underlying relationship than estimators that impose rigid structure on the underlying relationship. Second, we work with a large set of regressors, five different policy environment variables, and two measures of aid to help robustness checks on the policy/aid interaction effect on growth. Finally, our study is based on a panel data from a large number of countries in the developing world thus making our result reflective of the developing world.

We find that aid has a statistically significant impact on the growth rate of income in LDCs. The parametric specification that suggests a quadratic relationship between aid and income growth is not rejected by the LLKE estimator. However, unlike other research that finds a positive but diminishing returns to aid, we find the relationship to be U-shaped; at low levels, aid is negatively related to income growth but the relationship turns positive beyond a threshold level of aid. We find no statistically significant relationship between the policy environment and economic growth for most of our measures of policy, a result

that is different from those found in parametric specification of the aid/growth relationship. Unlike parametric specifications that find diminishing returns to aid, we find evidence of *increasing returns* to *aidgni*; at low levels, aid has no significant growth impact but it has significantly positive growth impact beyond a threshold level. This suggests that the popular parametric specification of the aid/growth relationship is generally appropriate and our results are consistent with studies that find a positive growth effect of aid.

The rest of the paper is organized as follows: Section 2 reviews the literature and briefly describes the growth equation we estimate, Section 3 describes the data and estimation method we use while Section 4 presents and discusses the statistical results. Section 5 concludes the paper.

2. PREVIOUS STUDIES AND MODEL

2.1. Previous Studies. The aid/growth literature is voluminous and has been growing at an exponential rate, especially after Burnside and Dollar’s (2000) paper. It is impossible to comprehensively review the literature in this paper, hence we briefly mention some of the studies relevant to this paper. Aid effectiveness research has generally reached one of three conclusions (Doucouliagos and Palman: 2005)²: (i) aid has positive growth effect, (ii) aid has no growth effect and may even be counterproductive, and (iii) aid has positive growth effect only if certain conditions are met in the recipient country

Building on Chenery and Strout’s (1966) two gap models and modern growth theory that emphasizes the importance of institutions, several studies conclude that aid has a positive growth impact. It does so by increasing investment, making it possible to import complementary inputs, increasing the productivity of existing inputs, or improving institutions and the policy environment. These studies fall into two sub-categories, categories we label as “unconditional effect” and “conditional effect”. Unconditional growth effect studies are those that find a growth effect without specifying any condition in the recipient country. Conditional growth effect studies are those that find a growth effect conditional on “good governance” or

“good policy” environment. Studies such as Gomanee *et al* (2005), Hansen and Tarp (2000), Irandoust and Ericsson (2005), Moreira (2005), Lensink and Morrissey (2001), among others are unconditional studies. Conditional growth effect studies include Burnside and Dollar (2000), Collier and Hoeffler (2004), Collier and Dollar (2002), Ruhashyinsk (2003), World Bank (1999), among others.

A second group of studies conclude that aid has no significant growth effect and that any effect that may have been found, is not robust to model specification, data, income level, or sample size (Easterly: 2003, Easterly *et al*: 2004, Roodman: 2004, Rajan and Subramania: 2005, among others). Finally, a sub-group of studies find a negative relationship between aid and income growth. The story is that aid allows countries to avoid necessary growth-enhancing but painful reforms (Boone: 1996, Heckleman and Knack: 2005, Djankov *et al*: 2006). Aid may also be used for increased consumption and possibly diverted for personal use instead of increasing investment or income generating activities, given the fungibility of aid resources. Large inflows of aid could also lead to currency appreciation which in turn leads to a reduction in exports, increased imports, and reduced economic growth (Tan: 2006,2007).

Most of the recent studies on the aid/growth relationship use panel data and dynamic panel estimator or some instrumental variable (IV) estimator to draw their conclusion. These studies therefore follow the popular parametric specification we mentioned above. However, as Rajan and Subrimanian (2005) point out, the results of GMM estimates depend on the choice of instruments, thus allowing different researchers to draw different conclusions based upon the choice of instruments. We use a nonparametric estimator in our study to obviate some of these problems.

2.2. Model. The growth equation we estimate is the cross-country growth equation that has been used by earlier researchers to investigate the aid/growth relationship so we do not spend time to develop the equation here.³ As in earlier research, our growth equation

includes initial per capita income (gdp_{cap_0}), investment ($gcfgdp$), export growth ($xgrow$), policy ($policy$), and (aid). We include $xgrow$ in the equation following the arguments of Feder (1983) and Balassa (1978). We also include $region$ to account for regional differences in the growth rate of per capita income. The growth rate equation we estimate is given as:

$$(1) \quad \begin{aligned} gdp_{capgr_{it}} = & \alpha_0 + \alpha_1 aid_0 + \alpha_2 gcfgdp_{it} + \alpha_3 xgrow_{it} + \alpha_4 gdp_{cap_{i,0}} + \alpha_5 region \\ & + \alpha_6 policy_{it} + \gamma_i + \delta_t + \varepsilon_{it} \end{aligned}$$

where γ_i , δ_t and ε_{it} are country specific, temporal, and idiosyncratic error terms, respectively, α_i s are coefficients to be estimated and all other variables are as defined above. It is customary to include the square of aid (aid_{sq}) as well as the interaction of aid and policy as additional regressors in the growth equation to account of non-linearities and interaction terms in the relationship, and we do so for the test of correct parametric specification. The LLKE uses the same regressors as the parametric model but does not restrict the nature of the relationship *a priori*, hence it includes quadratic as well as interaction terms among all variables.

There are several reasons why aid may affect economic growth in LDCs. Aid may supplement domestic resource mobilization hence higher rates of accumulation of physical as well as human capital (Gyimah-Brempong and Traynor: 1999). Second, aid may allow developing countries to import critically important inputs that will increase productivity as well as the utilization rates of existing capacity.⁴ Aid may also help to finance structural and institutional reforms. It is possible that aid will be accompanied by market friendly reforms. Our specification is similar to those of earlier researchers (Dalgaard and Hansen: 2005, Hansen and Tarp: 2001, Gormanee *et al*: 2005, Rajan and Subramanian (2005), among others).

It is however possible that aid could be diverted to personal use or used in non-productive activities, increase consumption and decrease resource mobilization (Boone: 1996), or increase the size of the bureaucracy (Easterly: 2003, Djankov *et al*: 2006). Aid inflows could also allow governments to avoid *necessary but painful* reforms or countries may not be able

to effectively *absorb* aid they receive (Aiyer and Ruthbah: 2008). In these cases, aid may have no positive growth impact and may even be counterproductive. Based on the foregoing, the literature has left the growth effect of aid as an empirical question to be determined by the data.

3. DATA AND ESTIMATION METHOD

3.1. Data. The dependent variable is the growth rate of per capita income ($gdpcapgr$). We measure $gdpcapgr$ as the annual growth rate of real per capita income in 2000 PPP in a country. We follow the literature and measure investment ($gcfgdp$) as the gross domestic fixed capital formation/GDP ratio of a country in a year. Other variables in the equation are the growth rate of exports ($xgrow$), the initial level of per capita income ($gdpcap_0$), and the policy environment ($policy$). We measure $gdpcap_0$ as the per capita real GDP in 2000 PPP at the beginning of the sample period while $xgrow$ is the annual growth rate of real export earnings of a country. This means that $xgrow$ could change as a result of a change in export *volume*, a change in export *prices* or a combination of both. To measure *region*, we divided the sample countries into three distinct regions of the world—Africa, Asia and the Middle East (AME), and Latin America and the Caribbean (LAC)—based solely on geography. Region1 indexes Africa, AME is indexed by region2, while LAC is indexed by region3.⁵

There are several possible ways to measure the policy environment (e.g. government consumption, inflation rate, budget deficit, and the World Bank’s Country Policy and Institutional Assessment ($cpia$)), none of which is perfect. Data on the most comprehensive of these measures, the $cpia$, was not available to us. We therefore present five measures of the policy environment: (i) political stability ($polstab$), the quality of governance ($govqual$), the quality of business regulation ($regqual$), the rule of law ($rulelaw$), and control of corruption ($corcont$). Each of these variables is a combination of several indicators that reflect a particular aspect of the policy environment. For example, $govqual$ combines the quality of public

service delivery, the quality of the bureaucracy, the competence and independence of the civil service and the credibility of the government's commitment to policies while *regqual* is a composite of measures that include free market policies such as price controls, bank supervision, and trade and business regulation.⁶ Each of these variables is scaled in such a way that it has a mean of zero, unit variance, and ranges from -2.5 to 2.5 with higher values indicating better policy environment.

The variable of interest in this study is aid. There are several possible ways to measure aid, including total aid inflow, aid commitment, and net aid disbursement. Total aid inflow does not account for the possibility that some of the aid inflow could be used to service debt hence not available for growth enhancing activities; it also does not account for differences in the sizes of countries. Aid commitment does not reflect the amount of aid that a country *receives* in a particular year since not all aid commitments in a year are disbursed in the same year. To account for differences in country size and the amount of aid a country *receives* in a particular year, we measure aid as the ratio of net aid disbursement to GNI (*aidgni*). As measured here, *aidgni* includes net aid disbursement from all sources (including bilateral and multilateral, public and private sources). We recognize that not all aid disbursement may be absorbed and spent. However, aid has to be disbursed if it is to be absorbed. In addition to *aidgni*, we use a second measure of aid defined as real net aid inflow per capita per year (*aidpercap*) in this study. *aidpercap* also accounts for differences in country size.

The data were obtained from various sources. *aidgni* and *aidpercap* were obtained from the Development Assistance Countries' (DAC) website at www.oecd.org/dac/stats.dac/ while *polstab*, *govqual*, *regqual*, *rulelaw*, and *corcont* were obtained from Matruzzi *et al*, *Governance Matters IV: Governance Indicators for 1996-2004*, (World Bank: 2006). The *Governance Matters IV* data are at two year intervals from 1996 to 2004. We interpolated the years in between in order to have full coverage for all years. Data for *gdpcap₀*, *gcfgdp*, and *xgrow* were obtained from World Bank, *World Development Indicators: 2005*, (Washington DC: World Bank). The data are for 77 developing countries for the 1996-2004 period covering

Africa, Asia and the Middle East and Latin America and the Caribbean.⁷ Our sample is a balanced panel data with 693 observations.

Summary statistics of the sample data are presented in Table 1. The mean growth rate of per capita income is 1.4% with a standard deviation of 3.85, suggesting a highly variable growth rate in the sample. The mean per capita GDP is about \$4,800, with a standard error of about \$4,900. Net aid flow as a percentage of national income in the sample is relatively high averaging about 5.68% with a standard error of 7.94 and ranges from -0.69% to 62.87%. The wide range of *aidgni* combined with the negative value at the lower bound of *aidgni* suggests a wide dispersion of net inflow of aid across countries in the sample and that some countries experienced net outflow of “aid”. The mean of *aidpercap* is about \$36.00 with a minimum of -\$21.67 and a maximum of \$389.45. An interesting aspect of the data is that the sample means of all policy variables are negative, suggesting that the countries, on average, had poor policy environments. The Pearson correlation coefficient between *aidgni* and *aidpercap*, on the one hand and per capita income growth on the other are 0.029 and 0.036, respectively. These correlation coefficients are significantly different from zero at $\alpha = .05$.

3.2. Estimation Method. Parametric regression modeling requires that one specify the functional form of the underlying object *prior to estimation*. Correctly specified parametric models provide consistent estimates of the object being estimated ($\sqrt{n}$ -consistent), while hypothesis tests based on such estimates are statistically valid, having actual levels equal to their assumed nominal levels. These properties do not hold for incorrectly specified models in general. One cannot overstate the importance of this issue: incorrectly specified parametric models will, in general, produce biased and inconsistent estimates; inference based on such models will be invalid. The concern in the current setting is that any analysis of the relationship between aid and income growth constructed from poorly specified parametric models may yield biased and unreliable estimates of the underlying relationship.

3.2.1. *Cross-Validated Local Linear Nonparametric Estimator.* One may instead choose to pursue non-parametric regression methods which are robust to functional specification since they allow the data to determine the appropriate model. Non-parametric methods are consistent under a fairly weak set of assumptions and are best suited to situations involving large data sets. Their application is not without cost, however, as non-parametric methods are computationally intensive and are *slower to converge* than correctly-specified parametric models (i.e. slower than the $\sqrt{n}$ rate of correctly specified parametric models).

We briefly describe the non-parametric estimator used herein.⁸ Consider a regression model given by

$$(2) \quad y_j = g(x_j) + u_j, \quad (j = 1, \dots, n)$$

where x_j is a set of regressors of dimension q . The unknown conditional expectation $g(\cdot)$ and its derivatives cannot be observed but can be consistently estimated using non-parametric methods. Define the derivative of $g(x)$: $\beta(x) \stackrel{def}{=} \nabla g(x) \equiv \partial g(x)/\partial x$ ($\nabla g(\cdot)$ is a $q \times 1$ vector). Define $\delta(x) = (g(x), \beta(x)')'$. $\delta(x)$ is a $(q + 1) \times 1$ vector-valued function whose first component is $g(x)$ and whose remaining q components are the first derivatives of $g(x)$. Taking a Taylor series expansion of $g(x_j)$ at x_i , we get $g(x_j) = g(x_i) + (x_j - x_i)'\beta(x_i) + R_{ij}$, where $R_{ij} = g(x_j) - g(x_i) - (x_j - x_i)'\beta(x_i)$. We write (2) as

$$(3) \quad \begin{aligned} y_j &= g(x_i) + (x_j - x_i)'\nabla g(x_i) + R_{ij} + u_j \\ &= (1, (x_j - x_i)')\delta(x_i) + R_{ij} + u_j. \end{aligned}$$

Kernel methods require selecting bandwidths, and for what follows this unknown bandwidth vector is selected using a data-driven method known as “least-squares cross-validation” to be defined below. We use $\hat{h}$ and $\hat{\lambda}$ to denote the cross-validation choice of h and λ that

minimizes (8) below. Having obtained an appropriate bandwidth vector $(\hat{h}, \hat{\lambda})$ we then estimate $\delta(x)$ by ($x \in R^q$ is a fixed point)

$$(4) \quad \hat{\delta}(x) = \begin{pmatrix} \hat{g}(x) \\ \hat{\beta}(x) \end{pmatrix} = \left[\sum_{i=1}^n \begin{pmatrix} 1, & (x_i - x)' \\ x_i - x, & (x_i - x)(x_i - x)' \end{pmatrix} K_{h,\lambda,ij} \right]^{-1} \sum_{j \neq i} \begin{pmatrix} 1 \\ x_i - x \end{pmatrix} K_{h,\lambda,ij} y_i,$$

where $K_{h,\lambda,ij}$ is defined in the Appendix, and we estimate $g(x)$ by

$$(5) \quad \hat{g}(x) = e_1' \hat{\delta}(x).$$

where e_1 is a $(q+1) \times 1$ vector whose first element is one with all remaining elements being zero.

Note that $\hat{g}(x)$ is the non-parametric estimate of the unknown conditional expectation $g(\cdot)$ while $\hat{\beta}(\cdot)$ is its derivative with respect to the regressors. In effect, we use fully non-parametric and data-driven methods to estimate the unknown conditional expectation ($g(\cdot)$) and its response ($\beta(\cdot)$). This local linear method has a valuable property: the more linear the underlying relationship the faster the rate of convergence (see Li and Racine: 2004). In fact, it is well known that if the underlying relationship is truly linear, this cross-validated local linear estimator can have a $\sqrt{n}$ rate of convergence. However, in general, we do not restrict the nature of the underlying relationship nor the rich interaction that might exist between regressors. Also, we do not restrict the response $\beta(\cdot)$ to be constant as would be the case with a simple linear model. All standard errors are obtained via resampling methods ('bootstrapping') to provide robust standard error estimates.

As noted above, we use least-squares cross-validation to select the bandwidth vectors h and λ . This is similar to minimizing the sum of squared residuals for a parametric regression model, however, to avoid overfitting we minimize a leave-one-out estimator. A leave-one-out local linear kernel estimator of $\delta(x_i)$ is obtained by a kernel weighted regression of y_j on

$(1, (x_j - x_i)')$ given by

(6)

$$\hat{\delta}_{-i}(x_i) = \begin{pmatrix} \hat{g}_{-i}(x_i) \\ \hat{\beta}_{-i}(x_i) \end{pmatrix} = \left[\sum_{j \neq i} \begin{pmatrix} 1, & (x_j - x_i)' \\ x_j - x_i, & (x_j - x_i)(x_j - x_i)' \end{pmatrix} K_{h,\lambda,ij} \right]^{-1} \sum_{j \neq i} \begin{pmatrix} 1 \\ x_j - x_i \end{pmatrix} K_{h,\lambda,ij} y_j.$$

In practice one should use a different h and λ for each different component of x , and for all applications conducted herein we allow h and λ to differ across variables through the use of multidimensional numerical search methods.

The leave-one-out kernel estimator of $g(x_i)$ is given by

$$(7) \quad \hat{g}_{-i}(x_i) = e_1' \hat{\delta}_{-i}(x_i).$$

We choose h and λ to minimize the least-squares cross-validation function (sum of squared leave-one-out estimation errors) given by

$$(8) \quad CV(h, \lambda) = \sum_{i=1}^n [y_i - \hat{g}_{-i}(x_i)]^2,$$

where $\hat{g}_{-i}(x_i)$ is defined in (7). The resulting bandwidth vector is denoted $(\hat{h}, \hat{\lambda})$.

For the current application we employ the fully non-parametric cross-validated local-linear estimator described above (see Li and Racine: 2004 for further details). The following are a few of the benefits of the application of this estimator to our data: (i) 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 available. (ii) When the underlying relationship is somewhat linear (‘almost linear’), the resulting non-parametric estimator can have a convergence rate that is arbitrarily close to the parametric rate (Li and Racine: 2004). (iii) The estimator *jointly* models the relationship among all variables thereby allowing us to readily exploit any interaction which may exist for the underlying relationship.

For purposes of comparison, we use Arellano and Bond’s Dynamic Panel Data (DPD) systems estimator (Arellano and Bond: 1991, Blundell and Bond: 1998) to estimate the

income growth equation in (1). This estimator produces consistent estimates in the presence of dynamics and endogenous regressors and has become the standard for estimating cross country growth regressions in recent studies. We use the two-step DPD estimator to estimate the growth equation.

4. RESULTS

Before we discuss the nonparametric estimates, we present the DPD estimates of the growth equation for purposes of comparison. These are presented in table 2.⁹ The coefficient estimate of *aidgni* is negative and significant at $\alpha = .01$ in all policy environments while that of *aidsq* is positive and significant at $\alpha = .01$ in all policy environments. Similarly, the coefficient of *aid* $\times$ *policy* is negative and significant while that of *aidsq* $\times$ *policy* is positive and significant at $\alpha = .01$ in all policy environments. Furthermore, the coefficient of *policy* is positive and significant at conventional levels of significance for all policy environments. The estimates suggest a quadratic relationship between aid and income growth. The positive and statistically significant coefficient on the policy/aid policy interaction also support the conditional effect hypothesis. The DPD estimates seem to be consistent with the popular parametric specification of the aid/growth relationship. While our sample supports a quadratic relationship between *aidgni* and income growth, we find *increasing returns* as opposed to decreasing returns to aid that has been found in the literature by the popular specification of the relationship. The coefficient estimates suggest an inverted U relationship between aid and income growth rate: at low levels, aid is negatively related to income growth but the relationship turns positive beyond a threshold level of aid.¹⁰

We use a nonparametric specification test to test for the appropriateness of the parametric specification of the growth equation.¹¹ The null hypothesis is that the equation is correctly specified. The test rejects the null hypothesis of correct specification at $\alpha = .025$ for the two measures of aid and all policy environments.

We now present a variety of nonparametric results for the income growth equation to see whether the popular parametric specification of the aid/growth relationship is appropriate and robust. In this flexible nonparametric setting, we investigate whether the robustness of the relationship between growth and aid depend on how one measures aid (*aidgni* versus *aidpercap*) or on the policy environment and if so whether it depends on how one measures the policy environment (*polstab*, *govqual*, *regqual*, *rulelaw*, *corcont*). We estimated 20 regressions (permutations of 2 measures of aid, 5 policy environments, and 2 plots for each permutation) using LLKE methods with cross-validated bandwidth selection employing 100 restarts of the numerical search algorithms to ensure that the bandwidth represented global minima. We computed partial regression and derivative surfaces for the aid/environment combinations. All standard errors and tests of significance are based on $B = 399$ bootstrap replications. The test of significance use the method of Racine (1997) and Racine, Hart and Li (2006), and we refer the reader to these papers for further details.

Because of space considerations, we only present plots of the combination of the two measures of aid (*aidgni*, *aidpercap*) and two measures of the policy environment (*govqual*, *rulelaw*).¹² When plotting the results, we trim the horizontal axes to reflect the 2.5 through 97.5 percentiles of the data.¹³ This is necessary to ensure that the error bounds associated with the tails of the data do not make it impossible to visually discern the underlying relationship for the bulk of the support of the data.

Interpreting nonparametric estimates is more involved than interpreting parametric estimates. A method we adopt is to consider the ‘partial regression’ ($\hat{g}(x_i)$) and ‘partial gradient’ ($\hat{\beta}(x_i)$) surfaces that measure how the dependent variable and its response surface change in response to changes in an explanatory variable, holding all other variables constant at their median values.¹⁴ All figures contain 95% error bars ($\hat{\beta}(x_i) \pm 2\hat{\sigma}(\hat{\beta}(x_i))$). Because all the plots in figures 1–8 have been configured to a common scale of the dependent variable, readers should be careful in interpreting the plots.

4.1. **AID/GNI Ratio.** The nonparametric results based on *aidgni* as our measure of aid are presented in figures 1–4 and table 3. Figures 1 and 3 present the plots of the partial regression surface while figures 2 and 4 present the plots of the partial gradient surface. The significance tests in table 3 indicate that *aidgni*, *gcfgdp*, *xgrow*, *govqual*, *region*, and *corcont* have statistically significant relationships with the growth rate of per capita income while *gdpcap₀*, *rulelaw*, *polstab*, and *regqual* have no statistically significant relationship with income growth. The plots in figures 1 and 2 show that *aidgni* is positively related to the growth rate of per capita income when the policy environment is government quality (*govqual*) holding all other variables at their sample medians/modes. The plots also show that the relationship is significantly different from zero as the derivative (i.e., gradient in the figures) estimates' 95% error bars generally exclude zero.¹⁵

The partial response surface plots in figure 2 also suggest that for the *govqual* policy environment, the aid/growth relationship is not constant throughout the support of the data. Conditional on other variables held constant at their medians, the aid/growth relationship is constant around 0.07 but gradually trends upwards when *aidgni* reaches 15%. The plots in figures 1 and 2 suggest that, at least for the *govqual* policy environment, while the aid/growth relationship may be quadratic given the support of the data, it does not exhibit diminishing returns that have been found by earlier researchers (e.g. Hansen and Tapp: 2000, 2001). On the contrary, it indicates increasing returns to aid. In this regard, our results differ from the results of research that find a significant growth effect but with diminishing returns. Our results also differ from the results of research that finds no significant relationship between aid and income growth.

Figures 3 and 4 present the estimates of the growth equation when policy environment is measured as *rulelaw*. As in the estimates for *govqual*, figure 3 presents the partial regression plots while figure 4 presents the partial gradient surface plots. The plots in figure 3 indicate that there is a positive and statistically significant relationship between *aidgni* and income growth rate when all other variables are held constant at their sample medians/modes.

The plots in Figure 4 indicate that the growth effect of *aidgni* remains constant at 0.10 until *aidgni* reaches 15; the relationship then gradually trends upwards. The structure of this relationship is similar to the aid/growth relationship when the policy environment is *govqual*. This confirms our earlier result that while there exists a non-linear relationship between *aidgni* and income growth, the relationship may suggest increasing returns rather than diminishing returns found by earlier researchers.

We draw two conclusions from the discussion of the plots in figures 1–4 and table 3. Holding all other variables at their sample medians, there is a positive and significant relationship between aid and the growth rate of income for all policy environments. The growth effects of aid is 0.10 on the average, and trends upwards after *aidgni* reaches 15%. In this regard, our results are similar to the results of studies that find a positive quadratic relationship between aid and income growth in LDCs (e.g. Hansen and Tarp: 2001, Gormanee *et al*: 2005). Second, we find that for some policy environments, the nature of the aid/growth relationship is nonlinear and exhibits increasing returns. This is the case when the policy environment is measured as government quality, political stability, or rule of law, while the relationship is linear when we measure the policy environment as regulatory quality or corruption control. The results differ from those that have been obtained in the literature.

Does the policy environment have any significant influence on the growth rate of income? The partial regression plots and the partial gradient surface plots presented in figures 1–4 indicate that there is a significantly positive relationship between the policy environment as measured by *govqual* and the growth rate of per capita income.¹⁶ This result is consistent with research results that find a positive growth effect of aid.

4.2. Aid Per Capita. We measured aid as *aidgni* in our analysis above. In this sub-section, we estimate the growth equation using aid per capita (*aidpercap*) as the measure of aid. The results are presented in table 4 and figures 5–8. As in the estimates based on *aidgni*, table 4 presents the nonparametric significance test results, while figures 5–8 present the partial

regression and partial gradient response plots. Figures 5 and 7 present the partial regression plots while figures 6 and 8 present the partial response surface plots, respectively. The regression results in table 4 indicate that most of the regressors are significantly related to the growth rate of income. However, the significance test indicates that the contribution of *aidpercap* to the explanation of income growth rate is statistically significant at $\alpha = .05$ only when the policy environment is *polstab*.

The partial regression plots presented in figures 5 and 7 indicate a positive relationship between income growth and *aidpercap* when the policy environment is as *govqual* or *rulelaw*. This may suggest that our result that aid has a positive growth impact, given the policy environment, is not affected by how we measure aid. However, the partial gradient surface plots presented in figures 6 and 8 indicate that the income growth/*aidpercap* relationship is not statistically significant at conventional levels for both policy environments. Therefore we cannot conclude that there is a significantly positive relationship between *aidpercap* and growth.¹⁷ We also do not observe the nonlinear relationship between *aidpercap* and income growth that we observed when we measured aid as *aidgni*. We conclude from this that there is generally no significant relationship between *aidpercap* and income growth rate, holding all other variables at their sample medians. The insignificant relationship between income growth and *aidpercap* shown in figures 5–8 is confirmed by the significance tests presented in table 4. This conclusion and the significantly positive relationship between income growth rates and *aidgni* we find above may suggest that the relationship between aid and income growth rate in empirical work may partly depend on how one measures aid as well as what policy environment conditions such relationship.

Conditional on *aidpercap* and other variables, the plots in figures 5–8 also reveal no significant positive relationship between income growth rate and the policy environment as measured by *govqual* and *rulelaw* since the 95% error bars include zero. Although not presented here, we also find no significant relationship between income growth and the policy environment. These conclusions are supported by the significance tests presented in table 4.

The plots in figures 5–8 also indicate the existence of significant regional and temporal differences in the growth rate of income, but no significant relationship between income growth rate and initial income level.

While the results we find in figures 5–8 are generally similar to those in figures 1–4, there are some *qualitative* differences. In general, we find no statistically significant relationship between *aidpercap* and income growth rates while we find a positive and statistically significant relationship between *aidgni* and income growth rates for all measures of the policy environment. Also, while we find a positive and statistically significant relationship between income growth rates on the one hand and *gfcgdp* and *xgrow* on the other for all levels of the latter two when *aidgni* is the measure, the relationship is not robust throughout the support of the data when *aidpercap* is the measure of aid.

Our results suggest that aid has a significant and positive impact on the growth rate of per capita income in LDCs. We find a quadratic relationship between aid and income growth rate. However, unlike the diminishing returns to aid found in the literature, we find evidence of *increasing returns* to aid. The aid/growth relationship also depend on the measurement of aid; *aidgni* has a significant effect on income growth while *aidpercap* has no significant growth effect. We also find no significant growth effect of some policy policy environment. Our fundamental conclusion is that the popular specification of the aid/growth as specified by earlier researchers (e.g. Hansen and Tapp: 2001, 2000, Hudson and Mosley: 2001, Dalgaard and Hansen: 2005, World Bank: 1998) is only partly correct. While we find a significant relationship between aid and income growth rate, our results do not support the diminishing returns to aid that have been found by other researchers. On the contrary, our results suggest that there may be increasing returns to aid. Our results are not generally consistent with the results of research that aid has a growth effect only if there is a good policy environment. The conclusion we draw is that the popular parametric specification is generally correct although the form of the quadratic relationship may not be correct.

Our findings have some implications for aid research as well as aid policy. First, the growth effect one finds may depend on how one measures aid. Researchers should therefore use caution when interpreting the results of studies of the relationship between aid and income growth. Second, we find that conditional on the measurement of aid, the policy environment generally has no significant effect on income growth. Though the LLKE does not provide a simple scalar measure of the growth effect of the interaction between aid and the policy environment, we *may* infer a growth effect from this interaction given that the estimator accounts for the interaction between aid and the policy environment during estimation. The growth impact of aid we find in this sample is generally very small—about 0.07, suggesting that LDCs cannot rely on massive infusions of aid to power their economic growth. One way of generating sustained growth in LDCs is to find ways to make aid *more* effective rather than arguing about whether it is effective or not.

5. CONCLUSION

This paper used the LLKE, a robust non-parametric estimator, and panel data from a large number of countries to investigate the correctness and robustness of a popular parametric specification of the aid/growth relationship. We find that aid has a significant positive effect on income growth in LDCs and that the aid/growth relationship is indeed quadratic. However, this quadratic relationship exhibits *increasing returns* rather than diminishing returns as the popular parametric specification suggests. This suggests that while the popular parametric specification of the aid/growth relationship is generally correct, one must be careful in the interpretation of the estimates. We note that the magnitude of the positive growth effect of aid we find in this study is very small (0.07). It is unlikely that aid will be the growth catalyst some proponents of aid argue it is. We also find that the relationship between *aidgni* and growth is not constant as the latter variable changes; there may be evidence of increasing returns to *aid*.

We also find that conditional on *aidgni*, there is a positive and significant growth relationship between the policy environment as measured by *government quality*, *political stability*, *rule of law*, *regulatory quality* or *corruption control*, respectively. The results are consistent with the results of studies that find a positive growth effect of external aid as well as those that find aid to be more effective given a more favorable policy environment. However, our results do not support the diminishing returns to aid found by some researchers in the literature. Our results may partly explain the inconsistent results of past research on the aid/growth relationship. Studies that measure aid as *aidgni* are likely to find significant relationships while those that measure aid as *aidpercap* are likely to find no significant relationship. We note that differences in the measurement of aid is not the only reason for differences in results as studies that use the same measure may come to different conclusions. Our results have implications for aid research as well as policy.

6. NOTES

1. According the DAC statistics, official development assistance (ODA) to developing countries fell to about 62.893 billion in 2000. Since then, there has been an upturn in the volume of ODA to developing countries, reaching a high of 78.362 billion in 2004.
2. For example, see the conclusions of Burnside and Dollar (2000) and Easterly, Levine and Roodman (2004).
3. Readers are referred to the literature on the subject, especially to Burnside and Dollar: 2000, Boone: 1996, Collier and Dollar: 2002, Easterly: 2003, Rajan and Subramanian: 2005, and Hansen and Tarp: 2001, among others.
4. These growth channels are consistent with the gap models discussed by Chenery and Strout (1966).
5. The numbering of the regions is arbitrary.
6. See Matruzzi *et al.* (2005) for details of the calculation of these indices.
7. The countries in the sample are Burundi, Benin, Burkina Faso, Bangladesh, Bahamas, Belize, Bolivia, Brazil, Botswana, Central African Republic, Chile, China, Cote d'Ivoire, Cameroon, Colombia, Congo, Costa Rica, Dominican Republic, Algeria, Equador, Egypt, Fiji, Gabon, Ghana, Guatemala, Guyana, Hong Kong, Honduras, Haiti, Indonesia, India, Israel, Jamaica, Jordan, Kenya, Cambodia, South Korea, Lebanon, Ethiopia, Lesotho, Morocco, Madagascar, Mexico, Malta, Mauritania, Malawi, Malaysia, Niger, Nigeria, Nicaragua, Nepal, Oman, Pakistan, Panama, Peru, Philippines, Papua New Guinea, Paraguay, Rwanda, Sudan, Senegal, Singapore, Sierra Leone, Slovenia, Suriname, Seychelles, Chad, Togo, Thailand, Trinidad and Tobago, Uganda, Uruguay, Tanzania, South Africa, Zambia, Zimbabwe. All nominal values were converted to 2000 PPP values. The sample countries and time frame used for this study are dictated by the availability of the requisite data.
8. In the interest of brevity we do not present the details; we refer the interested reader to Li and Racine (2004).

9. Because of space considerations, we only present the coefficients of *aid*, *aidsq*, and their interaction terms for all *policy*, environments. We also present estimates for *aidgni* only. Full results are available from the authors upon request.
10. See Gyimah-Brempong, Racine and Gyapong (2009) for the calculation of the threshold levels of aid.
11. Details of the test are provided in Appendix A.
12. See Li and Racine (2004).
13. The plots of the combinations of aid and the other policy environments (*polstab*, *regqual*, *corcont*) are available upon request.
14. This is necessary to avoid the undue influence of data sparsity.
15. See Li and Racine (2004) for more on the interpretation of LLKE estimates.
16. There are similarly positive relationships between income growth rates and *aidgni* when the policy environment is *corcont*, *regqual*, or *polstab*.
15. Although not shown, there is a positive and significant relationship between growth of per capita income and *corcont* but the relationship between income growth on the one hand and *polstab* and *regqual* on the other is not significant.
17. We find a positive but insignificant relationship between *aidpercap* and income growth rates when the policy environment is either *regqual* or *corcont* but a positive and significant growth effect when the policy environment is *polstab*.

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8. APPENDIX A: CONDITIONAL MOMENT SPECIFICATION TEST

Out of concern that the parametric model (1) may not be correctly specified, we apply the test for correct parametric specification (Hsiao, Li, & Racine (2007)) to the fully parametric model. Briefly, this is a consistent conditional moment test. We are interested in testing the null hypothesis that a parametric model is correctly specified which we state as

$$(9) \quad H_0 : P[E(y_i|x_i) = m(x_i, \gamma)] = 1,$$

where $m(\cdot)$ is a known function (the assumed parametric regression model) with γ being a $p \times 1$ vector of unknown parameters. The alternative hypothesis is the negation of H_0 , i.e.,

$$(10) \quad H_1 : P[E(y_i|x_i) = m(x_i, \gamma)] < 1.$$

We therefore employ a test statistic that is based on $I \simeq E[u_i E(u_i|x_i) f(x_i)]$, where $u_i = y_i - m(x_i, \gamma)$ and where $f(\cdot)$ is a joint PDF. Note that $I = E\{[E(u_i|x_i)]^2 f(x_i)\} \geq 0$, and $I = 0$ if and only if H_0 is true. Therefore, I serves as a valid candidate for testing H_0 .

The sample analogue of I is

$$(11) \quad \begin{aligned} I_n &= n^{-1} \sum_{i=1}^n \hat{u}_i \hat{E}_{-i}(u_i|x_i) \hat{f}_{-i}(x_i) = n^{-1} \sum_{i=1}^n \hat{u}_i \left\{ n^{-1} \sum_{j=1, j \neq i}^n \hat{u}_j K_{h,\lambda,ij} \right\} \\ &= n^{-2} \sum_i \sum_{j \neq i} \hat{u}_i \hat{u}_j K_{h,\lambda,ij}, \end{aligned}$$

where $\hat{u}_i = y_i - m(x_i, \hat{\gamma})$ is the residual obtained using the parametric null model, $K_{h,\lambda,ij}$ is a generalized product kernel that admits categorical and continuous datatypes and h and λ are the bandwidth vectors for the categorical and continuous datatypes, respectively, $\hat{\gamma}$ is a $\sqrt{n}$ -consistent estimator of γ (under H_0), and $\hat{E}_{-i}(u_i|x_i) \hat{f}_{-i}(x_i)$ is a leave-one-out kernel estimator of $E(y_i|x_i) f(x_i)$. We use a wild-bootstrap to obtain the test statistic's null distribution.

Application of this test *rejects* the null that model (1) or the model including the quadratic and interaction terms noted earlier is the correct parametric specification ($P < 0.0025$). Given that this common parametric specification is rejected by the data, we choose instead to proceed with the non-parametric approach of Li & Racine (2004).

APPENDIX A. TABLES AND FIGURES

TABLE 1. Summary Statistics of Sample Data

Variable	Mean*	Standard Deviation	Minimum	Maximum
<i>aidgni</i> (%)	5.6785	7.9450	-0.6889	62.8655
<i>aidpercap</i> (PPP ₂₀₀₀)	35.82	45.81	-21.61	389.45
<i>xgrow</i> (<i>xgrow</i>) (%)	6.5275	14.5164	-43.7045	123.8283
<i>gdpcapgr</i> (<i>y</i>) (%)	1.4295	3.8451	-19.4642	25.1583
<i>gdpcap</i> (<i>y</i>) (PPP ₂₀₀₀)	4842.36	4926.02	453.19	25784.06
<i>gcfgdp</i> (<i>k</i>) (%)	21.7205	7.9829	0.2105	61.8511
<i>polstab</i>	-0.3414	0.8829	-2.78	1.52
<i>govqual</i>	-0.2478	0.7732	-2.59	2.59
<i>requal</i>	-0.0678	0.7663	-2.91	2.31
<i>rulelaw</i>	-0.2863	0.7412	-2.31	2.24
<i>corcont</i>	-0.2844	0.7241	-1.68	2.51
N	693			

TABLE 2. DPD Estimates of Growth Equation: AIDGNI

Variable	Coefficient			Estimates	
	Regqual	Polstab	Rulelaw	Corcont	Govqual
<i>aidgni</i>	-0.3641*** (6.83) ⁺	-0.5213*** (10.99)	-0.3898*** (7.06)	-0.4049*** (5.94)	-0.5101*** (8.88)
<i>aidsq</i>	0.0134*** (8.55)	0.0175*** (12.73)	0.0155*** (8.22)	0.0173*** (4.55)	0.0154*** (12.07)
<i>policy</i>	1.7466*** (5.69)	1.9088*** (7.13)	1.6752*** (8.22)	1.3169*** (11.77)	1.9831*** (8.63)
<i>aid</i> × <i>policy</i>	-0.2711*** (5.99)	-0.2903*** (10.87)	-0.2008*** (4.56)	-0.2475*** (7.11)	-0.3754*** (10.43)
<i>aidsq</i> × <i>policy</i>	0.0228*** (5.71)	0.0227*** (10.81)	0.0098*** (4.93)	0.0169*** (8.84)	0.0298*** (9.98)
<i>threshold</i> (%) ⁺⁺	14.36	9.39	9.53	6.57	11.49
N	693				
F	276.73	156.73	165.44	187.53	193.19
2nd ord. ser. cor.	-1.608	-0.378	-0.25	0.08	-0.18
Hansen test	37.65 [48]	39.80 [48]	37.22 [48]	36.43 [48]	42.71 [48]
Hausman <i>m</i>	89.21 [8]	62.78 [8]	78.92 [8]	82.77 [8]	68.92 [8]

+ absolute value of “t” statistics in parentheses. * 2-tail significance at $\alpha = 0.10$

** 2-tail significance at $\alpha = 0.05$ *** 2 tail significance at $\alpha = 0.01$

⁺⁺ Level of *aidgni* at which $\partial growth / \partial aid = 0$. It is obtained by solving for $\partial y / \partial aidgni = 0$ at the means of the policy variables and *aidgni*.

TABLE 3. Test of Significance: AIDGNI

Variable	p value				
	rulelaw	govqual	polstab	regqual	corcont
<i>year</i>	0.00***	0.007***	0.002***	0.018*	0.01**
<i>region</i>	0.00***	0.002***	0.00***	0.00***	0.00***
<i>aidgni</i>	0.001**	0.03**	0.01**	0.021*	0.08*
<i>gcfgdp (k)</i>	0.00***	0.00***	0.022*	0.03*	0.01**
<i>loggdpcaplag (y_{t-1})</i>	0.4511	0.82	0.228	0.51	0.89
<i>xgrow (xgrow)</i>	0.00***	0.00***	0.00***	0.00***	0.00***
<i>polstab</i>			0.69		
<i>govqual</i>		0.0325**			
<i>regqual</i>				0.31	
<i>rulelaw</i>	0.3283				
<i>corcont</i>					0.04*
N	693				

+ absolute value of “t” statistics in parentheses. * 2-tail significance at $\alpha = 0.10$

** 2-tail significance at $\alpha = 0.05$ *** 2 tail significance at $\alpha = 0.01$

TABLE 4. Test of Significance: Aid Per Capita

Variable	p value				
	rulelaw	govqual	corcont	regqual	polstab
<i>year</i>	0.005**	0.002**	0.005**	0.003**	0.002**
<i>region</i>	0.00***	0.002**	0.00***	0.00***	0.00***
<i>aidpercap</i> (PPP_{2000})	0.85	0.20	0.11	0.29	0.005**
<i>gcfgdp</i> (k)	0.03*	0.12	0.07*	0.09*	0.005**
<i>loggdpcaplag</i> (y_{t-1})	0.52	0.15	0.99	0.56	0.97
<i>xgrow</i> ($xgrow$)	0.00***	0.00***	0.00***	0.00***	0.00***
<i>polstab</i>					0.83
<i>govqual</i>		0.19			
<i>regqual</i>				0.35	
<i>rulelaw</i>	0.98				
<i>corcont</i>			0.98		
N	693				

+ absolute value of “t” statistics in parentheses. * 2-tail significance at $\alpha = 0.05$

** 2-tail significance at $\alpha = 0.01$ *** 2 tail significance at $\alpha = 0.001$

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FIGURE 1. aidgni/govqual partial regression plots.

FIGURE 2. aidgni/govqual partial gradient plots.

FIGURE 3. `aidgni/rulelaw` partial regression plots.

FIGURE 4. `aidgni/rulelaw` partial gradient plots.

FIGURE 5. aidpercap/govqual partial regression plots.

FIGURE 6. aidpercap/govqual partial gradient plots.

FIGURE 7. aidpercap/rulelaw partial regression plots.

FIGURE 8. aidpercap/rulelaw partial gradient plots.