Is the Relationship Between Aid and Economic Growth Nonlinear?

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Abstract

In this paper, we investigate the relationship between foreign aid and growth using recently developed sample splitting methods that allow us to simultaneously uncover evidence for the existence of heterogeneity and nonlinearity. We also address model uncertainty in the context of these methods. We find some evidence that aid may have heterogeneous effects on growth across two growth regimes defined by ethnolinguistic fractionalization. However, when we account for model uncertainty, we find no evidence to suggest that the relationship between aid and growth is nonlinear. In fact, our results suggest that the partial effect of aid on growth is likely to be weakly negative. In this sense, our findings suggest that aid is potentially counterproductive to growth with outcomes not meeting the expectations of donors.

Keywords: Foreign aid, Economic growth, Threshold Regression, Classification and Regression Trees

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1. Introduction

One of the most controversial debates in the empirical growth literature with big policy implications is whether foreign aid is beneficial to a country's economic growth. In an influential paper, Burnside and Dollar (2000) examine the effect of aid, as measured by the ratio of the sum of grants and the grant equivalents of official loans in constant prices to real GDP (or, Effective Development Assistance (EDA)), on growth. Using standard cross-country panel growth regressions that include an interaction term of aid with a policy index, they find that aid has a positive impact on growth in developing countries as long as these countries have sound macroeconomic policies. The policy implication of this finding was straightforward. Policy makers at international aid agencies could now argue that development assistance can contribute to poverty reduction in countries with good policy environments.

On the other hand, this finding has sparked an industry of mainly empirical papers trying to examine the sensitivity of Burnside and Dollar's results to model specification, alternative sets of included/excluded variables, and different data series. Some of the most notable papers include Guillaumont and Chauvet (2001), Hansen and Tarp (2001), Collier and Dehn (2001), Collier and Dollar (2002, 2004), Collier and Hoeffler (2004), Easterly (2003), Easterly, Levine, and Roodman (2004), Dalgaard, Hansen and Tarp (2004), Roodman (2004), and Rajan and Subramanian (2005a,b). Some of these papers confirm the main finding of Burnside and Dollar; i.e., that aid is effective only in countries with good policies, while others find the results fragile to the addition of particular variables.

One problem that the literature on aid and growth has been dealing with is the problem of how to model heterogeneity and/or nonlinearities in growth analyses. Typically, what has been done is to treat this issue in an ad hoc way by including squares and interaction terms for aid, policy, and other growth variables. The unsystematic, ad hoc nature as to how specific choices are made over which nonlinearities/heterogeneity to include and which to leave out, however, leaves much to be desired. For instance, there is no good reason for only including an interaction term between aid and policy and not the square of aid or even both in the model. Why not also include an interaction term between policy and institutions? In fact, several new growth theories such as Azariadis and Drazen (1990) and Howitt and Mayer-Foulkes (2002) suggest that the cross-country growth process is highly nonlinear.

To make things worse, as suggested by Brock and Durlauf (2001), new growth theories are inherently open-ended. By theory open-endedness, Brock and Durlauf refer to the fact that typically the a priori statement that a particular theory of growth is relevant does not preclude other theories of growth from also being relevant. Growth models typically do not provide much guidance as to the exact specification in which growth determinants should enter the growth equation as well. Brock and Durlauf point out that taken together, the combination of theory and specification uncertainty (what they refer to collectively as model uncertainty) potentially renders coefficient estimates of interest to be “fragile”. The potential fragility of coefficient estimates under model uncertainty is important because it implies that findings on the relationship between aid and growth, which do not properly account for model uncertainty, may be non-robust. For instance, the finding of a nonlinear relationship between aid and growth may, in fact, be just a manifestation of some other unaccounted misspecification due to omitted variables or even due to unaccounted heterogeneity and/or nonlinearities with respect to other growth determinants. Our point is that strong a priori assumptions on the appropriate specification of growth determinants and functional form of the model are hard to justify.

Nevertheless, while there is little agreement over the exact nature of nonlinearities and heterogeneity in the growth literature, there is a growing consensus that, given that we think such nonlinearities/heterogeneity exists, they may potentially be fruitfully modeled using empirical tools that emphasize pattern recognition (see Durlauf (2003)). Sample splitting and threshold regression methods and their derivatives are important constituents of such tools. For instance, Durlauf and Johnson (1995) employed a classification and regression tree method (CART; see Breiman, Friedman, Olsen, and Stone (1984)) to sort countries based on initial per capita income and initial literacy rates. They interpret their findings as evidence in favor of the theory of poverty traps of Azariadis and Drazen (1992).

In this paper we employ recently developed sample splitting methods to systematically uncover the robust relationship between aid and growth. Sample splitting methods such as threshold regression and regression trees allow for increased flexibility in functional form and at the same time are not as susceptible to curse of dimensionality problems as nonparametric methods. Unlike parametric models with polynomial terms (squares, interactions, etc), sample splitting methods are parsimonious. More importantly, these methods are structurally interpretable as they endogenously sort the data, on the basis of some threshold determinants, into groups of countries each of which obeys the same model (i.e., multiple growth regimes). Other notable applications of sample splitting methods in growth include Tan (2006) who use an improved regression tree algorithm to CART (GUIDE; see Loh (2002)) and Masanjala and Papageorgiou (2004) who employ threshold regression (TR; see Hansen (1996, 2000) and Gonzalo and Pitarakis (2002)).

A major problem associated with the sample splitting methods that have been employed so far in the literature, however, is the sequential nature of the splitting process. By this we mean that choices of threshold variables and split values made in initial sample splits are never revised as the number of splits increases. Hence, any mistake made at the earlier stages of the process is propagated to the splits below. The result is that the classification of observations into regimes can be unstable. Small changes in the data result in large changes to the threshold or "tree" structure (see Hastie, Tibshirani, and Friedman (2001) and also Hong, Wang, and Zhang (2005)).

To be clear this is not an issue of statistical inference but rather it has to do with the qualitative nature of threshold variables. It is one thing to define a 95% confidence interval for a (real-valued) parameter as [0.3,0.8] and quite another thing to say that a 95% confidence interval for the discrete-valued parameter associated with the choice of threshold variable includes two variables, initial per capita income and property rights. In the former case the threshold effect is consistent with theories of poverty traps and development while in the latter it says something about the importance of economic institutions in posing barriers to growth.

A contribution of this paper is to employ a simultaneous sample split method, Bayesian tree regression (BTREED; see Chipman, George, and McCulloch (1998, 2002)) to deal with this problem. BTREED is a non-sequential regression tree procedure that generates the best tree of every size. Thus, it is less likely to suffer from some of the consequences (e.g., tree instability issues) of sequential sample splitting methods such as TR or CART. Nevertheless, we compare our results with TR since this method provides formal asymptotic theory for the construction of confidence intervals for the threshold estimates.

A second key methodological contribution of this paper is to move the discussion away from model selection towards model averaging in the context of nonlinear (and, in particular, sample split or tree) models. As Cohen-Cole, Durlauf, and Rondina (2006) note, there has not so far been a systematic investigation of model uncertainty and nonlinearities in the growth context. This paper can be viewed as a first attempt towards this ambitious goal. In order to achieve this, we exploit a new statistical learning methodology, Bayesian Additive Regression Trees (BART)[1]. Specifically, the idea is to generate a large number of trees, each of which is a bad fit for the data as a whole (i.e., a “weak learner”), but gives insight into a small part of the underlying data generation process, so that, taken together, the “sum-of-trees” provides a good estimate of the underlying process. Also, in contrast to single-tree methods, there is no need in BART to condition upon a particular choice of slope covariates and threshold variables. Rather inference is obtained by averaging the sum-of-tree draws from the BART posterior distribution. We view our methodological contribution in this paper as an extension of the standard model averaging exercises recently applied in the empirical growth literature (see Brock and Durlauf (2001), Fernandez, Ley, and Steel (2001), and Sala-i-Martin, Doppelhofer, and Miller (2004) among others).

We find some evidence in the BTREED and TR results that aid may have heterogeneous effects on growth across two growth regimes defined by ethnolinguistic fractionalization. In particular, countries that belong to a growth regime characterized by levels of ethnolinguistic fractionalization above a threshold value experience a negative partial relationship between aid and growth, while those in the regime with ethnolinguistic fractionalization below the threshold experience no growth effects from aid at all. We also find that countries in the regime with higher levels of ethnolinguistic fractionalization experience, on average, lower growth rates than countries in the lower ethnolinguistic fractionalization regime. Nevertheless, we do find substantial tree instability in our sample split exercises so that attempts to characterize the typology of these growth regimes with a high degree of certainty remains elusive. There is evidence that the typology of these regimes may be alternatively well-characterized by property rights institutions or macroeconomic policies such as the level of inflation, and not just ethnolinguistic fractionalization. The data simply cannot be certain.

Our BART results are therefore particularly valuable given the high degree of uncertainty generated by tree instabiliity. Here, we find very little evidence to suggest that the relationship between aid and growth is nonlinear for the set of developing countries who are aid recipients. Overall, our results suggest that the partial effect of aid on growth is very likely to be negative although we cannot reject the hypothesis that aid has no effect on growth. In this sense, our findings suggest that aid is potentially counterproductive to growth with outcomes not meeting the expectations of donors. We are therefore sympathetic to the positions of work such as Easterly, Levine, and Roodman (2004) and Rajan and Subramanian (2005a) which are generally pessimistic about the potential contributions of aid to improving economic performance.

The remainder of the paper is organized as follows. In Section 2 we briefly describe our econometric methodology, which includes Bayesian tree regression (BTREED), threshold regression (TR), and Bayesian Additive Regression Trees (BART). In Section 3 we describe our data. Section 4 presents our findings and Section 5 concludes.

[1] BART is closely related to so-called “ensemble” methods such as random forests (Breiman (2001)), bagging (Breiman (1996)), and, most directly, boosting (Friedman (2001)) in the machine learning literature. Ensemble methods have been shown to have extremely good out-of-sample prediction performance besting even those of neural networks (see, in particular, Friedman (2001) and Hastie, Tibshirani, and Friedman (2001)). Unlike the above-mentioned machine learning methods, however, BART is not defined purely by an algorithm, but, instead, by a statistical model within the Bayesian framework.}, developed by Chipman, George, and McCulloch (2002).

2. Econometric Methodology

We conduct our analysis of the relationship between aid and growth using a generalized sample split model that can be defined as follows:

$$g_i = \alpha_j + h_i\beta_j + x_i'\gamma_j + \varepsilon_i \quad \text{iff} \quad z_i \in R_j\left(\{\lambda_s\}_{s=1}^{b-1}\right) \quad \text{for} \quad j = 1,\dots,b \qquad (1)$$

where *i* indexes the observations (i.e., countries) and *j* indexes the *b* growth regimes. g_i is the average growth rate of per capita income for country *i* across a time period. h_i is the foreign aid proxy (i.e., the variable of interest). We distinguish between two sets of growth determinants. The *k*-dimensional vector x denotes the set of slope covariates while the *p*-dimensional vector z denotes threshold variables.

The set of slope covariates includes the usual Solow regressors, that is, the logarithms of the average rates of physical and human capital accumulation, the logarithm of average population growth rate plus 0.05, and the logarithm of initial per capita income. We also include variables from a wide range of new growth theories including macroeconomic policy, geography, ethnolinguistic fractionalization, political institutions, and property rights institutions. Most of the covariates can also be viewed as threshold variables. For instance, theories of development that emphasize threshold externalities such as Azariadis and Drazen (1992) suggest that initial per capita income may act as a threshold variable. Alternatively, theories that emphasize economic “take-off” (e.g., Galor and Weil (2000), Galor and Moav (2002), and Galor (2005)) suggest an important role for fundamental growth determinants (such as geography and institutions) in driving growth divergence[2]. To be as agnostic as possible a slope covariate is also a threshold variable as long as it makes sense.

To this end, we specify in our sample split exercises that, with the exception of the factors of accumulation and population growth rates (which are period averages), all slope covariates (including aid) are also threshold variables. The set of parameters is given by $\Psi = \left(b, \{\lambda_s\}_{s=1}^{b-1}, \Theta\right)$, where $\Theta = \left(\alpha_j, \beta_j, \gamma_j, \sigma_j^2\right)_{j=1}^{b}$ is the set of regression parameters, *b* is the number of regimes, and $\{\lambda_s\}_{s=1}^{b-1}$ is the set of threshold parameters that define the set of threshold splits. Note that $\{\lambda_s\}_{s=1}^{b-1}$, in effect, partitions the support of the threshold variables Z into *b* mutually exclusive regions $\{R_j\}_{j=1}^{b}$.

We can visualize an example of a tree or threshold regression estimation procedure using Figure 1 which is due to Hastie, Tibshirani, and Friedman (2001). Here, the set of observations is partitioned into five regimes, $R_1,\dots,R_5$, defined by the interaction between variables x_1 and x_2. In this example, the model in (1) is modified to be a piece-wise constant model so that a local average is estimated within each regime. The model we use to analyze the effect

[2] “The timing of the “take-off” may differ significantly across countries and regions due to historical accidents, as well as variation in geographical, cultural, social and institutional factors, trade patterns, colonial status, and public policy that have affected the relationship between human capital formation and technological progress [Galor, 2005, p. 80]”.

of aid on growth will be inkeeping with (1); i.e., it will be a piece-wise linear model. That is, we would replace each "step" in Figure 1 with a plane in each growth regime which slope is determined by the coefficients to the local augmented neoclassical growth model defined by (1).

It is worth noting the generality of (1). If we ignore the effects of z on growth; that is, if we specify, a priori, a single growth regime, then we are back to the canonical growth regressions of Mankiw, Romer, and Weil (1992) and Barro (1996). However, as pointed out by Brock and Durlauf (2001), such a formulation ignores prior knowledge regarding the existence of heterogeneity across country units. That is, it ignores the possibility that the effect of the right-hand side covariates on growth may differ systematically across groups of countries. Brock and Durlauf explore a special case of (1) to study the robust heterogeneous effects of ethnolinguistic fractionalization on growth. In their paper, the number of regimes b is trivially fixed to two as their threshold variable is a single dummy variable for Sub-Saharan Africa. Given the binary nature of the dummy variable there is no need to estimate a threshold parameter and hence the classical inference is still valid[3]. In contrast, our methodology enables us to have multiple regimes and multiple threshold variables. This is very important in our context given the large number of growth determinants that can act as threshold variables. What is more, the number of regimes b is not pre-specified, but instead is endogenously determined.

One way to estimate (1) is to use the threshold regression methodology of Hansen (2000). At each stage of the sample splitting, we carry out Hansen's test to see whether the sample should be split. If so, we choose the best (in the sense of minimizing sum of squared errors) threshold variable, associated threshold value estimate, and the set of regression estimates for Θ. The same procedure is then applied iteratively to each of the two subsequent subsamples. This "tree growing" procedure stops when either the null of no-split fails to be rejected, or the number of observations in the (sub-)sample falls below a pre-determined minimum value. It is worth noting that TR bears deep similarities to the classification and regression trees (CART) method of Breiman, Friedman, Olsen, and Stone (1984). The added advantage of using threshold regression as opposed to CART is that the statistical inference[4] for both the threshold and the regression slopes has been well developed by Hansen (2000).

Its primary weakness, however, lies in the instability of trees to small perturbations in the data as well as in the way that variables are defined. It has been well-documented that small changes in the data can lead to very different threshold variables, threshold values, and even number of regimes being selected by sample splitting methods (see, Hastie, Tibshirani, and Friedman (2001) and also Hong, Wang, and Zhang (2005)). A major reason for the instability of trees is due to the sequential nature of typical sample splitting algorithms. That is, the tree building method does not "update" the tree as it gets bigger. Therefore, it may be that as the tree gets bigger, the previously selected threshold variables and split values in the "upper" parts of the tree (i.e., the initial sample splits) are no longer optimal. We should note that Bai

[3] However, this is not true anymore when the threshold variable is not binary and we need to estimate a threshold parameter because the threshold parameter is not identified under the null. Hansen (2000) shows that the inference is non-standard and develops an asymptotic theory for both the threshold parameter and the regression slopes including a method to construct asymptotic confidence intervals for the former.

[4] It should be noted that Hansen (2000) only claims the validity of these results for the single threshold (i.e., two-regime) case, even though he has shown examples of proceeding with these tests iteratively beyond this case.

(1999) had suggested an alternative method for getting around the sequential nature of traditional threshold regression models. He calls this method “repartitioning”. The idea is to revise upper parts of the tree once lower parts of the tree are estimated. However, we found the practical implementation of repartitioning to be computationally expensive and quickly lost computational tractability even when the tree size was only moderately large. This led us to consider instead Bayesian tree regression (BTREED) developed by Chipman, George, and McCulloch (1998, 2002).

BTREED is not a sequential splitting method. Instead, what BTREED does is to search through trees of all sizes (i.e., the (final) number of regimes) and then locate the tree with the highest evidentiary weight for each size. Specifically, it employs MCMC to stochastically search over the posterior distribution of trees for high posterior probability trees. We then select the final tree using BIC. Because each of these trees (no matter the size) is generated probabilistically at every stage of tree building, we do not have the situation, as we do with sequential splitting methods such as TR, where “upper” portions of the tree are never revised even as we vary (increase) the size of trees[5]; see Chipman, George, and McCulloch (2002).

Nevertheless, we should note that BTREED, like TR, is still ultimately a model selection algorithm. Both sample split methods seek to present one tree as the best device for summarizing the relationship between growth and the set of growth determinants out of the forest of possible trees. While engaging in such model selection has advantages --- for instance, it allows us to present a structurally interpretable typology (i.e., tree diagram) for relating aid to growth --- this strategy ignores the evidentiary weight associated with alternative trees. Cohen-Cole, Durlauf, and Rondina (2006) have suggested that, even in the context of nonlinear models, researchers should still attempt to report robust estimates of relationships that take into account alternatives to the chosen or benchmark model. We pursue this suggestion in this paper. That is, we attempt to combine the evidentiary weight on the effect of aid on growth across a large number of tree models.

To do so, we employ a new methodology due to Chipman, George, and McCulloch (2005) known as Bayesian Additive Regression Trees (BART). More precisely, we do not condition on a particular choice of slope covariates and threshold variables but rather inference is performed by averaging posterior information across a large number of tree models in order to flexibly estimate the average effect of a variable of interest on the dependent variable.

Formally, if we define $w_i = \left(h_i, x_i, z_i\right)$, then we can write the growth model (1) as

$$g_i = f\left(w_i\right) + \varepsilon_i \qquad (2)$$

where $\varepsilon_i \mid w_i \sim N\left(0, \sigma^2\right)$ and $f\left(w_i\right) = E\left(g_i \mid w_i\right)$. Then BART provides a way to estimate (1) by combining information across tree models drawn from the posterior distribution, $\mu\left(m \mid w\right)$,

$$\hat{f}\left(w_i\right) = \sum_{m=1}^{M} \hat{f}_m\left(w_i, T_m, \Theta_m\right) \qquad (3)$$

[5] In fact, key steps in BTREED's stochastic tree building algorithm; i.e., “swap” and “change” split decisions (see Chipman, George, and McCulloch (1998, 2002)), are in the spirit of Bai's “repartitioning”.

Here, the *j*-th regime for each of the *M* trees T_m, $m = 1,...,M$, is associated with a real parameter θ_j. Hence, any w_i is associated with one of the θ_j within each tree. Letting $\Theta = (\theta_1, \theta_2, ..., \theta_b)$ where *b* is the number of regimes in *T*, a single tree model may be denoted by the pair (T, Θ). Let $\hat{f}(w_i, T_m, \Theta_m)$ denote the θ_j associated with w_i in the *m*-th tree. The posterior distribution for tree models, $\mu(m|w)$, is given by Bayes rule,

$$\mu(m|w) \propto \mu(w|m)\mu(m) \tag{4}$$

so that each weight is the product of the likelihood of the data given a model, $\mu(w|m)$, and the prior probability for a model, $\mu(m)$. The latter is implicitly given by,

$$\begin{aligned} \mu(1,...,M) &= \mu((T_1,\Theta_1),(T_2,\Theta_2),...,(T_M,\Theta_M),\sigma) \\ &= \mu(T_1,T_2,...,T_M)\,\mu(\Theta_1,\Theta_2,...,\Theta_M \,|\, T_1,T_2,...,T_M)\,\mu(\sigma) \end{aligned} \tag{5}$$

For computational reasons we follow Chipman et al and assume independence so that,

$$\mu(1,...,M) = \mu(\sigma)\prod_{j=1}^{M}\mu(T_j)\mu(\Theta_j \,|\, T_j) \tag{6}$$

BART samples from the above posterior distribution using a Markov Chain Monte Carlo (MCMC) algorithm. The construction of each tree T_m for $m = 1,...,M$ employs precisely the tree-building algorithm of BTREED. However, each tree is constrained to be small by appropriately setting the tree priors. The choice of parameter priors are also essentially similar to those of BTREED. Specifically, they are the normal-inverse gamma conjugate priors for the special case where the growth model is constrained to just estimating a constant term θ_j. We refer the reader to Chipman, George, and McCulloch (2005) for details.

For better approximations, we would want to set *M* to be relatively large. In our exercises, we follow Chipman et. al. and set *M* = 200. Notice that BART is greatly more flexible than (1). To see this consider first the case of *M* = 1, then $f_1(w_i, T_1, \Theta_1)$ is the conditional mean of g given w. However, when *M* > 1, the terminal node parameters are merely components of the conditional mean of g given w. Furthermore, these terminal node parameters will represent direct and indirect effects (interaction terms) depending on sizes of the trees. In the special case where every terminal node assignment depends on just a single component of w, the sum-of-trees model reduces to a simple additive function of splits on the individual components of w.

To assess the effect of each of the determinants on growth we use Friedman's (2001) partial dependence plot. To do so, first rewrite $f(w)$ as $f(h, h_c)$ where h_c is the complement of h in the set w. To estimate the (partial) effect of \$h\$ on growth, Friedman suggests that we average out the effect of h_c on growth; i.e.,

$$\begin{aligned} E(g \mid h) &= E_{h_c}\left[E(g \mid w)\right] \\ &= E_{h_c}\left[f(h, h_c)\right] \\ &= \int f(h, h_c)\, p(h_c)\, dh_c \end{aligned} \tag{7}$$

However, when the data is *i.i.d.*, then, we can approximate (7) with,

$$\hat{f}_h(h) = \frac{1}{N}\sum_{i=1}^{N} f\left(h, h_{c,i}\right) \tag{8}$$

where each h_c for $i = 1, \ldots, n$ is an observation in the data. The above is the prediction by BART of the partial dependence of growth rates on h at each level in its support. The pointwise posterior 95% confidence intervals for $\hat{f}_h(h)$ can also be easily obtain from its posterior distribution using the 2.5-th and 97.5-th percentiles of the MCMC draws.

One weakness that applies to all sample splitting methods is that there are almost no results on dealing with endogeneity. A notable exception is Caner and Hansen (2004) who develop a two-stage instrumental variable estimation procedure for threshold regression when the slope variables are endogenous but the threshold variable is exogenous. A more attractive estimator would consider the endogeneity of both slope and threshold variables. However, such an estimator would require an alternative estimation approach due to the nonlinear nature of the endogeneity. Unfortunately, an estimator for the case when both the slope and threshold variables are endogenous does not currently exist.

This lack of results for how to deal with endogeneity is a particularly important weakness in our context because we introduce aid as both a slope covariate as well as a potential threshold variable in this paper. The reason we do so is to capture possible differential impacts of aid on growth for countries above or below a threshold level of aid. Such a specification potentially describes the position of aid proponents who argue that aid needs to be at a high enough level before it has a positive impact on growth. However, by doing so endogeneity becomes a potential problem since aid is not randomly assigned to recipient countries. Typically, more aid is given to those who are less developed leading to potential bias in the estimation of regression coefficients because of problems with reverse causality as well as correlation with unobserved heterogeneity.

Another aspect of the problem is that the use of instrumental variables in the context of growth may be invalid; see Brock and Durlauf (2001). For an instrumental variable of aid to be valid, one has to assume that it is uncorrelated with all the omitted growth determinants. However, the inherent open-ended nature of growth theories makes this event unlikely. To explain their position, Brock and Durlauf considered the paper by Frankel and Romer (1999) on trade and growth. Using similar reasoning let us consider here the paper of Rajan and Subramanian (2005a). Rajan and Subramanian argue that since aid is clearly endogenous, then it is necessary to use instrumental variables to obtain consistent estimates for the effect of aid on growth. Their instrumental variables include dummies for colonial relationships involving Britain, France, Spain and Portugal as well as dummies that indicate whether the donor and recipient are common members of, or signatories to, an Entente or Alliance. However, notice that the recent growth literature provides many theories of how colonial status may affect institutions. Rajan and Subramanian do not account for any of these theories and hence it is plausible that the colonial dummies are correlated with the omitted growth determinants (regression error) rendering their instrumental variable method invalid.

In sum, there is no doubt that aid is potentially endogenous. Nevertheless, controlling for endogeneity in the context of aid and growth is a difficult task mainly for two reasons. First, current estimation procedures of sample splitting models are unable to deal with endogeneity in general. Second, the open-ended nature of growth theories present unique difficulties for researchers arguing for the validity of instruments. For these reasons, this paper should be viewed as a step towards getting the facts straight rather than making strong structural claims.

3. Data

We use an unbalanced panel dataset (see Table 4) over two periods 1965-79 (42 countries) and 1979-94 (56 countries) based on a broad set of cross-country growth variables. As discussed in the previous section, the dependent variable in (1) is the average growth rate of real per capita GDP corresponding to the two periods. The set of explanatory variables includes a time dummy for the time period 1979-94 and the canonical Solow variables; i.e., the logarithm of the sum of average population growth plus 0.05 for net depreciation, the logarithm of the average proportion of real investments (including government) to real GDP, the logarithm of years of male secondary and higher school attainment, and the logarithm of real per capita GDP for the initial year of the time period. The national accounting data used to construct these data series are obtained form Penn World Table 6.1 (see, Heston, Summers, and Aten (2002)), while schooling data comes from Barro and Lee (2001).

To proxy foreign aid we use data on Effective Development Assistance (EDA) as a share of real GDP constructed by Easterly, Levine, and Roodman (2004) and revised by Roodman (2004). Other studies have also measured aid flows using OECD data for net Overseas Development Assistance (net ODA). Net ODA is defined as transfers --- essentially, any assistance, save military aid, with a grant element of at least 25% --- from a donor minus any repayment during a given period. We chose to use EDA data (by Chang, Fernandez-Arias, and Serven (1999)) instead of ODA data in thhis paper for the same reason that Easterly et al. (2004), Roodman (2004), and others do so. As pointed out by Chang, et. al. the net ODA data potentially overstates the level of assistance to recipient countries. Instead, they propose to exclude technical assistance, which tend to go primarily to consultants instead of governments, and to account for different degrees of concessionality in loans.

The EDA data we employ is the most current version of the panel data used in much of the aid-growth literature (see, for instance, Burnside and Dollar (2000), Hansen and Tarp (2001), Dalgaard, Hansen and Tarp (2004)). This panel data set is available in 5-year periods from 1970-1999. Previously, aid data were only available every 4 years. We use the 5-year panel data set to construct average measures of EDA for the two sample periods 1965-79 and 1980-94.

Following the literature on growth and aid we include four macroeconomic policy variables. We include the logarithm of inflation rate plus one, the ratio of budget surplus to GDP, money supply (M2), and the Sachs-Warner (1995) variable measuring openness to trade. It is worth noting that we deviate from Burnside and Dollar who include a single measure of economic policies. Burnside and Dollar first estimate a growth regression without aid but with all the covariates and three indicators of macroeconomic policy --- log (1+inflation), budget balance to GDP, and the Sachs-Warner (1995) variable. Then, they construct their policy measure by forming a linear combination of the three using the coefficients as weights. We believe that the inclusion of generated regressors in the analysis will result in unnecessary biases so we include all four variables, instead (see also, Lubotsky and Wittenberg (2006)).

Additionally, we expand the Solow space with fundamental determinants of economic growth that include proxies for geography, ethnolinguistic fractionalization, political institutions, and property rights institutions. Following Rodrik, Subramanian, and Trebbi (2004) and Sachs (2003) we proxy geography using a climate variable that measures the percentage of a country's land area classified as tropical and subtropical via the Koeppen-Geiger system (KG Tropics) and a variable that measures the percentage of a country's land area that lies within the geographic tropics (TROPICAR; Gallup, Sachs, and Mellinger (1999)). We also include a variable of geographic isolation or the degree of landlocked-ness that measures the percentage of a country's land area within 100km of an ice-free coast (LCR100KM). To proxy the effect of ethnolinguistic fractionalization we use two measures due to Alesina et al (2003). We include a variable of racial and linguistic characteristics (ethnic fractionalization) and a measure of linguistic fractionalization (language). To capture tensions between social groups, we also include a measure of ethnic tensions from the International Country Risk Guide. Furthermore, we proxy political institutions using the average of Freedom House index of political rights (see Barro (1991)) while for property rights we use the ratio of assassinations to GDP (see Banks (2002)), a measure of the risk of expropriation of private investments (see Acemoglu, Johnson, and Robinson (2001), executive constraints (Polity IV), and\ a composite governance index (KKZ96; see Kaufmann, Kraay and Mastruzzi (2005)). Finally, we include time dummies and regional dummies for East Asia, Sub-Saharan Africa, and Latin America and the Caribbean to account for time and regional heterogeneity, respectively. Please refer to Table 1 for a detailed description of variables. Table 2 provides some summary statistics.

4. Results

4.1 Multiple Regimes and Foreign Aid

We first turn to our sample splitting (TR and BTREED) results. These methods require us to pre-specify which growth variables should be treated as slope covariates, which as potential threshold variables, and finally which as both. We carried out exercises for many alternative specifications. Our aim in carrying out these different exercises is to observe two forms of robustness. Firstly, we want to see if the trees obtained by TR and BTREED are stable. That is, we investigate whether the uncovered tree structures do not vary dramatically across specifications when we (1) vary the set of covariates, (2) given a set of covariates, vary the choices on which variables should be threshold variables, split variables, or both, and (3) vary the number of observations in the data due to the inclusion or exclusion of countries because of variations in missing values across specifications. And secondly, we want to see the extent to which the results obtained by these different sample splitting methods --- TR (sequential) and BTREED (non-sequential) --- are in agreement.

We report results for three specifications --- Baseline, Solow, and Parsimonious --- that turned out to be most interesting. The Baseline specification is meant to reflect closely the cross-country growth equation in the aid literature (see Burnside and Dollar (2000)). The set of slope covariates includes the Solow variables (i.e., population growth, investment, schooling, and initial income), aid (EDA), macroeconomic policy variables (i.e., openness, inflation, budget surplus, M2), geography (i.e., TROPICAR), linguistic fractionalization (language), regional dummies, political institutions (political rights), and property rights (assassinations, expropriation risk, executive constraints, governance (KKZ96)). The set of threshold variables includes most of the slope variables. We do not include in this set the rates of human and physical capital accumulation and population growth rates because these are period averages and not initial conditions.

The Solow specification differs from the Baseline specification in that the set of covariates only includes the Solow and the Aid variables. Following Durlauf, Kourtellos, and Minkin (2001), the idea behind the Solow specification is to examine local generalizations of the Solow model in the sense that a Solow model applies to each country within a growth regime, but the model's parameters vary across regimes.

Finally, the Parsimonious specification aims to maximize the number of observations by excluding the macroeconomic policy variables. Specifically, the set of slope covariates includes population growth, investment, schooling, initial income, aid, TROPICAR, language, political rights, governance (KKZ96), and the three regional dummies. The set of threshold variables for the Parsimonious specification comprises TROPICAR, language, political rights, givernance (KKZ96), aid, and initial income.

Figures 2(a)-(c) show the tree diagrams for BTREED for, respectively, the Baseline, Solow, and Parsimonious specifications, while Figures 3(a)-(c) show the corresponding diagrams for TR. We also report Hansen's 95% confidence bounds in Figures 4(a)-(c); these correspond to the TR threshold value estimates in Figures 3(a)-(c). While the tree structures generated by TR in Figures 3(a)-(c) offer us an interpretable relationship between various growth determinants and economic growth, the confidence bounds provide us with a measure of the uncertainty over the classification of particular countries into each growth regime. The classification of countries into regimes is given, for both BTREED and TR and for all three specifications, in Table 4. Where applicable (i.e., in the TR cases), a superscript “c” denotes countries within Hansen's 95% confidence bounds for the first threshold split as given in Figures 4(a)-(c). Finally, the coefficient estimates and standard errors for each of the BTREED growth regimes are given in Table 5. The corresponding numbers for the TR growth regimes are given in Table 6.

4.1.1 Analysis of Baseline Tree Diagrams

Our Baseline results for BTREED and TR are essentially in agreement. In terms of the tree structures, comparing Figure 2(a) with Figure 3(a), we find that both BTREED and TR identify two growth regimes defined by ethnolinguistic heterogeneity (language). The size of the regimes are roughly equal. We also note that the regime with ethnolinguistic heterogeneity falling below the threshold value (regime (1)) is initially richer and has a faster rate of per capita income growth on average than the regime where ethnolinguisitc heterogeneity falls above the threshold value (regime (2)). If we look at the country breakdowns for the regimes; please refer to columns 1 and 4 of Table 4, we find that the breakdowns are also very similar for both BTREED and TR. Those countries for which the two are not in agreement --- i.e., Algeria and Zimbabwe --- fall within Hansen's 95% confidence bounds.

The countries in the high ethnolinguistic fractionalization growth regime are predominantly Sub-Saharan African countries (with the key exception of Botswana which is classified as belonging to the other regime). On the other hand, the low ethnolinguistic fractionalization growth regime is composed mostly of Latin American and Caribbean countries (with the exception of Paraguay and possibly Guatemala). The countries in Asia, Europe, North Africa, and the Middle East have more heterogeneous predicted growth experiences. While most countries in Asia appear to fall in the worse performing (high ethnolinguistic fractionalization) regime, some such as Bangladesh, China, South Korea, and Papua New Guinea are predicted to fall in the better performing (low ethnolinguistic fractionalization) group. Similarly, while most countries in the set that we label for convenience as Europe, North Africa, and the Middle East are classified as belonging to the better performing (low ethnolinguistic fractionalization) regime, there are notable exceptions such as Iran and Israel that get placed into the worse performing (high ethnolinguistic fractionalization) regime.

The finding that ethnolinguistic fractionalization is an important driver of heterogeneity in growth is consistent with work by Easterly and Levine (1997) and Alesina et. al. (2003). Easterly and Levine, in particular, argue that ethnolinguistic fractionalization is critically important in accounting for Sub-Saharan Africa's underdevelopment. Given that the set of countries in this study are necessarily confined to the set of developing countries (aid recipients), the fact that almost all Sub-Saharan African countries (with the lone and well-documented exception of Botswana (see, for instance, Acemoglu, Johnson, and Robinson (2003))) are separated out in this way and classified under the worse performing regime would appear to provide especially strong support for Easterly and Levine's hypothesis.

4.1.2 Baseline Parameter Estimates for Multiple Growth Regimes

The evidence on the nature of the growth regimes has important implications for the recent debates over the effect of aid on growth. In contrast to the current literature, our Baseline results suggest that the effect of aid on growth (if any) does not depend on policy variables but rather depends on the fundamental determinant, ethnolinguistic fractionalization. Specifically, columns 1 and 2 of Table 5 (for BTREED) and Table 6 (for TR) provide the results for the two growth regimes for the respective sample split methods. We find that aid has no significant effect for countries in the regime with low ethnolinguistic fractionalization, but, has a negative and highly significant (at the 1% level) effect for countries in the regime with high ethnolinguistic fractionalization. Since the countries in the latter regime are, on average, initially poorer to begin with, our results suggest that aid is in fact potentially counter-productive for this set of countries. Our results therefore are consistent with Easterly, Levine, and Roodman (2004) and Roodman (2004).

In terms of the coefficient estimates and standard errors for growth determinants, the results in Tables 5 and 6 are revealing. For both BTREED and TR, we find that the coefficients to initial per capita income for countries in both the high and low ethnolinguistic fractionalization growth regimes are highly significant at the 1\% level and negative. A negative coefficient on log initial income per capita is typically taken as evidence in the literature that poorer countries within the regime are catching up with richer countries in the same regime after controlling for other growth factors. Our findings are therefore consistent with the interpretation in the literature of “conditional convergence” within each of the two growth regimes. In this sense, the findings appear to suggest the existence of two convergence clubs defined by ethnolinguistic fractionalization, where countries within each club are converging to a different steady state.

Both BTREED and TR find that climate (TROPICAR) has a significant negative effect on growth for countries in both regimes, while property rights institutions (expropriation risk) exhibit a significant positive relationship for both regimes. Macroeconomic policies also appear to be important for countries in the worse performing (high ethnolinguistic fractionalization) regime. For instance, conditional on the other growth determinants, countries with higher rates of inflation experience significantly lower growth rates in this regime. Finally, the Solow variables; i.e., population growth, investment, and schooling, are all significant and have the correct signs; that is, negative, positive, and positive, respectively, for countries in the worse performing (high ethnolinguistic fractionalization) regime, although they are insignificant for countries in the low ethnolinguistic fractionalization regime.

In sum, the findings from the Baseline specification, which is meant to reflect the literature at large, would appear so far to be stable --- in the sense that both BTREED and TR are in agreement --- and reflect the consensus of the recent work on the relationship between aid and growth. Nevertheless, we would like to go a step further in order to investigate whether the results we obtained for the Baseline specification holds when we perturb the exercises a bit. We turn now, therefore, to the results for the Solow and Parsimonious specifications.

4.1.3 Results from Alternative Specifications

Figures 2(b) and 3(b) show the tree diagrams for BTREED and TR, respectively, for the Solow specification. Recall that the only difference between the Solow and Baseline specifications is that, except for aid and the canonical Solow variables, all other variables that were pre-assigned to be slope covariates in the Baseline setup are now assigned to be solely potential threshold variables. As can be seen, the tree diagrams for the Solow specification are dramatically different from those obtained for the Baseline specification. The BTREED tree for the Solow specification is split into two regimes. But, now, the threshold variable selected is no longer ethnolinguistic fractionalization, but inflation. Furthermore, the set of countries within each regime also differs dramatically from what we obtained before. There are now 85 observations in one regime (the low inflation regime) and 13 in the other (the high inflation regime) as opposed to 49 for both under the Baseline specification. Also, as far as the breakdown of countries into regimes is concerned (see column 2 of Table 4), there does not appear to be such a strong separation according to geographic regions as we obtained before. Essentially, a few countries from each regional grouping with particularly high levels of inflation are picked out to form the high inflation regime. Nevertheless, if we look at the estimates for the relationship between aid and growth (see columns 4 and 5 of Table 5), we see that it is (negative but) insignificant from zero for both regimes. These results, therefore, should not be taken as evidence to support the position that aid may be beneficial to those developing countries who are made to implement desirable macroeconomic policies as precondition to receiving aid (policy conditionality).

The situation for TR is worse. As can be seen from Figure 3(b), TR now splits the set of countries into five growth regimes according to institutions and geography. These are the low-quality institutions regime (regime (1)), the medium-quality institutions/less tropical regime (regime (2)), medium-quality institutions/more tropical regime (regime (3)), the high-quality institutions/less geographically accessible regime (regime (4)), and the high-quality institutions/more geographically accessible regime ((regime (5)). The classification of countries into regimes is therefore not at all similar to what was achieved before under the Baseline specification. However, if we consider the classification of observations for the Solow specification according to just the first split; i.e., according to whether or not expropriation risk for countries are above or below the threshold value of 0.455, then, the sample splits obtained under TR are somewhat similar to those obtained under BTREED. For instance, if we compare the country breakdown for the first regime in TR with the second regime in BTREED (i.e., compare columns 2 and 4 of Table 4), we see that these are largely similar. Therefore, at least at some level, we find that BTREED and TR do agree on the classification of countries into regimes.

However, even if we are willing to concede that, we cannot escape from the fact that BTREED and TR do not agree on the exact source of heterogeneity. Given the same choices for possible threshold variables, BTREED chooses macroeconomic policies (i.e., inflation) while TR chooses institutions (expropriation risk). It is therefore very difficult to assign a consistent structural interpretation to these findings.

The tree diagrams for the Parsimonious specification bear somewhat better news. Recall that the difference between the Parsimonious specification and the Baseline and Solow specifications is that for the Parsimonious specification, we drop the set of policy variables (except for aid). The reason we did so was to attempt to maximize the number of observations in the sample. If we compare the TR tree for the Parsimonious specification (Figure 3(c)) with that for the Baseline specification (Figure 3(a)), we see that they are identical. However, when we carry out the analogous comparison for BTREED (i.e., cf. Figure 2(c) with Figure 2(a)), we find that BTREED has selected a single regime (no heterogeneity) model for the Parsimonious specification. Hence, yet again, there is no clear message from our tree diagrams.

In other unreported exercises where we consider alternative choices for designating variables as threshold, slope, or both for these three specifications, we find very little evidence of tree stability. As represented by the trees in Figures 2(a)-(c) and 3(a)-(c), we find that the trees we obtain tend to (1) vary in size, (2) classify countries quite differently, and (3) choose different threshold variables; occasionally by fundamental determinants (such as geography, institutions, or ethnolinguistic fractionalization) and other times by policy variables (such as aid, inflation, or government budget surplus). The instability of the trees obtained under both BTREED and TR renders attempts to interpret them structurally to be, unfortunately, precarious. We are forced to conclude that there is very little evidence of a robust/reliable typology that would relate aid to growth. Another way of putting this is that we are severely limited in our ability to engage in tree (model) selection in any sensible way.

Nevertheless, there are some strong regularities in the results across specifications (please refer to Tables 5 and 6). We find that the relationship between aid and growth tends to be negative with most cases being significant. The exception is to be found in the high-quality institutions/less geographically accessible regime (regime (4)) for the Solow specification where the relationship between aid and growth appears to be positive and highly significant. Also, consistent with the larger debate in the growth literature over the importance of institutions versus geography to economic performance, we find that, at least for the set of developing countries in our sample, both these fundamental determinants are important to growth. Climate (TROPICAR) has a significant negative effect on growth for countries across specifications and regimes with the sole exception of the high ethnolinguistic fractionalization regime (regime (2)) for the Parsimonious specification for which its effect is also negative but insignificant. Similarly, property rights institutions (as measured by expropriation risk and governance (KKZ96)) have a significant positive effect on growth for countries in all regimes and for all specifications. We also find that conditional convergence holds strongly in the growth regression. For almost all regimes across all specifications (the exception being regime (2) of the Solow specification), we find the coefficient to initial per capita income to be negative and highly significant.

4.2 Robust Relationship between Aid and Growth

These regularities are encouraging because they suggest that even though the instability of the trees we obtained implies that finding one that would be robust enough to tell a structurally interpretable story about the relationship between aid and growth may be difficult, there may be a way for us nevertheless to give policymakers some sense of a “robust” relationship between growth determinants of interest, such as aid, and growth. As described in the Econometric Methodology section above, we attempt to uncover such robust relationships using partial dependency plots generated using the BART algorithm.

Figure 5(a) shows the partial (i.e., conditioning upon heterogeneity in terms of the other covariates) dependency plot of growth on aid for the Baseline/Solow set of variables. Similarly, the top left-hand graph in Figure 6 shows the partial dependency plot of growth on aid for the Parsimonious set of variables. We also show the corresponding MCMC posterior 95% confidence bounds around the point estimates in both figures. We find that the (partial) relationship between growth and international aid is probably not nonlinear, and very likely negative. Nevertheless, the posterior 95% confidence bounds do not allow us to reject the possibility that the relationship is flat.

The rest of Figures 5 and 6 show the partial dependence plots for the other growth variables and growth for the respective sets of variables (i.e., Baseline/Solow and Parsimonious). While some of these partial dependence plots --- notably those for ethnolinguistic fractionalization (language) --- are suggestive of possible nonlinear relationships, the large posterior 95% confidence bounds make it difficult for us to find conclusively in favor of this outcome. Taken together with the sample split (i.e., TR and BTREED) results, the evidence for a nonlinear relationship between ethnolinguistic fractionalization and growth appears to be the strongest amongst the set of regressors.

Like Figures 2(a) and 3(a) for the Baseline model, the partial dependence plots for ethnolinguistic fractionalization suggest that there exists a positive relationship between growth and ethnolinguistic fractionalization when the degree of fractionalization is low (below approximately 0.45), and a negative relationship when the degree of fractionalization is high (above 0.45).

The plots also show the correct relationships, as suggested by the neoclassical growth model, between the Solow variables and growth; i.e., negative for population growth, positive for investment and schooling, and negative for initial per capita income. They confirm the regularities from the TR and BTREED findings that property rights institutions (expropriation risk and governance (KKZ96)) have strong positive relationships with growth while climate (TROPICAR) has a strong negative relationship. Finally, policies such as trade openness and inflation also appear to have (positive and negative, respectively) consequences for growth.

5. Conclusion

In this paper, we attempt to characterize the relationship between aid and growth using recently developed sample splitting methods such as Bayesian tree regression (BTREED) and threshold regression (TR). Our aim is to uncover the factors that cause divergent effects, if any, of aid on growth for particular subsets of countries. We also sought evidence of a nonlinear relationship between aid and growth. While our results are suggestive of an interaction effect between ethnolinguistic fractionalization and aid --- so that countries with levels of ethnolinguistic fractionalization above a threshold value experience a negative relationship between aid and growth, while those with ethnolinguistic fractionalization below the threshold experience no growth effects --- our efforts are severely complicated by the high degree of tree instability, and therefore model uncertainty, associated with these sample splitting methods.

A key methodological contribution of our paper therefore is to implement in the growth context a strategy for obtaining robust characterizations of the aid/growth nexus using model averaging methods such as Bayesian Additive

Regression Trees (BART). When we do so, we find no evidence of a nonlinear relationship between aid and growth. The relationship between aid and growth is, in fact, likely to be negative. Our findings therefore leave us skeptical as to any potential positive contributions to growth from increasing foreign aid to developing countries. Nevertheless, the evidence from the data is noisy (as seen from the large posterior 95% confidence bounds we obtained), and we therefore expect the debate over the role of foreign aid in promoting growth to continue.

An additional caveat to the interpretation of our findings is the problem of the endogeneity of aid. The problem of endogeneity is one that is endemic to the growth literature. The standard method for getting around endogeneity is to use instrumental variables. However, instrumental variables estimation procedures for sample splitting methods are scarce and non-existent for the case of interest here (i.e., where we have endogeneity in the threshold variables). Further, as argued by Brock and Durlauf (2001), the open-ended nature of growth theories present difficulties for researchers arguing for the validity of instruments on the grounds of predetermination. We therefore suggest that our findings, while strongly consistent with recent findings in the literature, be interpreted with appropriate caution.

References

Acemoglu, D., J. A. Robinson, and S. Johnson (2001), "The Colonial Origins of Comparative Development: An Empirical Investigation," *American Economic Review*, 91, 1369-1401.

Acemoglu, D., J. A. Robinson, and S. Johnson (2003), "An African Success Story: Botswana," in In Search of Prosperity: Analytical Narrative on Economic Growth, edited by Dani Rodrik, Princeton University Press.

Alesina, A., A. Devleeschauwer, W. Easterly, S. Kurlat, and R. Wacziarg (2003), "Fractionalization," *Journal of Economic Growth*, 8(2), 155-94.

Azariadis, C. and A. Drazen (1990), "Threshold Externalities in Economic Development," *Quarterly Journal of Economics*, 105, 501-526.

Bai, J., (1997), " Estimating Multiple Breaks One at a Time," *Econometric Theory*, 13, 315-352.

Banks, A. (2002), Cross-National Time-Series Data Archive. Bronx, NY: Databanks International.

Barro, R. J. (1991), "Economic Growth in a Cross-Section of Countries," *Quarterly Journal of Economics*, 106(2), 407-43.

Barro, R. J. and J-W Lee (2001), "International Data on Educational Attainment: Updates and Implications," *Oxford Economic Papers*, 53(3), 541-63.

Breiman, L. (1996), "Bagging Predictors," *Machine Learning*, 26, 123-140.

Breiman, L. (2001), "Random Forests," *Machine Learning*, 45, 5-32.

Breiman, L., J. H. Friedman, R. A. Olsen, and C. J. Stone (1984), Classification and Regression Trees, Wadsworth, Belmont.

Brock, W. and S. Durlauf, (2001), "Growth Empirics and Reality," *World Bank Economic Review*, 15, 2, 229-272.

Burnside, C. and D. Dollar (2000), "Aid, Policies, and Growth," *American Economic Review*, 90(4), 847-868.

Chang, C. C., E. Fernandez-Arias, and L. Serven (1999), "Measuring Aid Flows: A New Approach," Washington: World Bank, Development Economics Research Group.

Chipman, H., E. George, and R. McCullough (1998), "Bayesian CART Model Search," *Journal of the American Statistical Society*, 93, 935-960.

Chipman, H., E. George, and R. McCullough (2002), "Bayesian Treed Models," *Machine Learning*, 48, 299-320.

Chipman, H., E. George, and R. McCullough (2005), "BART: Bayesian Additive Regression Trees," University of Chicago GSB mimeo.

Collier, P. and J. Dehn (2001), "Aid, Shocks, and Growth," World Bank Policy Research Working Paper No. 2688.

Cohen-Cole, E., S. N. Durlauf, and G. Rondina (2005), “Nonlinearities in Growth: From Evidence to Policy; Foreign Aid and Macroeconomic Policy,” University of Wisconsin SSRI Working Paper 2005-09.

Collier, P. and D. Dollar (2002), “Aid Allocation and Poverty Reduction,” *European Economic Review*, 46 (8), 1475-1500.

Collier, P. and D. Dollar (2004), ``Development Effectiveness: What Have We Learnt?” *Economic Journal*, 114 (496), F244-F271.

Collier, P. and A. Hoeffler (2004), “Aid, Policy and Growth in Post-Conflict Countries,” *European Economic Review*, 48, 1125-1145.

Dalgaard, C-J, H. Hansen, and F. Tarp (2004), “On The Empirics of Foreign Aid and Growth,” *Economic Journal*, 114(496), F191-F216.

Durlauf, S. N. and P. Johnson, (1995), “Multiple Regimes and Cross-Country Growth Behavior,” *Journal of Applied Econometrics*, 10, 4, 363-384.

Durlauf, S. N., A. Kourtellos, and A. Minkin (2001), “The Local Solow Growth Model,” *European Economic Review*, 45(4-6), 928-940.

Durlauf, S. N. (2003), “The Convergence Hypothesis After 10 Years,” University of Wisconsin SSRI Working Paper #2003-06.

Easterly, W. and R. Levine (1997), “Africa's Growth Tragedy: Policies and Ethnic Divisions,” *Quarterly Journal of Economics*, 112 (4), p.1203-50.

Easterly, W. (2003), “Can Foreign Aid Buy Growth?” *Journal of Economic Perspectives*, 17(3), 23-48.

Easterly, W., R. Levine, and D. Roodman (2004), “New Data, New Doubts: A Comment on Burnside and Dollar's “Aid, Policies, and Growth”,” *American Economic Review*, 94(3), 774-780.

Fernandez, C, E. Ley, and M.F.J. Steel (2001), “Model Uncertainty in Cross-Country Growth Regressions,” *Journal of Applied Econometrics*, 16(5), 563-576.

Friedman, J. H. (2001), “Greedy Function Approximation: A Gradient Boosting Machine,” *Annals of Statistics*, 29, 1189-1232.

Gallup, J., J. D. Sachs, and A. Mellinger (1999), “Geography and Economic Development,” *International Regional Science Review*, 22(2), 179-232.

Galor, O. and D. N. Weil (2000), “Population, Technology and Growth: From the Malthusian Regime to the Demographic Transition,” *American Economic Review*, 90, 806-828.

Galor, O. and O. Moav (2002), “Natural Selection and the Origin of Economic Growth,” *Quarterly Journal of Economics*, 117, 1133-1192.

Galor, O. (2005), “Unified Growth Theory: From Stagnation to Growth,” in Aghion, P. and S. N. Durlauf, eds., Handbook of Economic Growth, Elsevier: Amsterdam.

Guillaumont, P. and L. Chauvet (2001), “Aid and Performance: A Reassessment,” *Journal of Development Studies*, 37(6), 66-92.

Gonzalo, J and J. Pitarakis (2002), “Estimation and Model Selection based Inference in Single and Multiple Threshold Models,” *Journal of Econometrics*, 110, 319-352.

Hansen, B. E. (1996), “Inference When a Nuisance Parameter Is Not Identified under the Null Hypothesis,” *Econometrica*, 64(2), 413-30.

Hansen, B. E. (2000), “Sample Splitting and Threshold Estimation,” *Econometrica*, 68(3), 575-604.

Hansen, H. and F. Tarp (2001), “Aid and Growth Regressions,” *Journal of Development Economics*, 64(2), 547-570.

Hastie, T., R. Tibshirani, and J. H. Friedman (2001), The Elements of Statistical Learning, Springer-Verlag.

Heston A., R. Summers and B. Aten (2002), Penn World Table Version 6.1, Center for International Comparisons at the University of Pennsylvania (CICUP).

Hong, Y., D. Wang, and X. Zhang (2005), “Identifying Threshold Effects and Typologies in Economic Growth: A Panel Approach,” IFPRI Working Paper.

Howitt, P., and D. Mayer-Foulkes (2002), “R&D, Implementation and Stagnation: A Schumpeterian Theory of Convergence Clubs,” NBER Working Paper No. 9104.

Kaufmann, D., A. Kraay and M. Mastruzzi (2005), “Governance Matters IV: Governance Indicators for 1996-2004,” The World Bank, mimeo.

Loh, W.-Y. (2002), ''Regression Trees with Unbiased Variable Selection and Interaction Detection,” *Statistica Sinica*, 12, p. 361-386.

Lubotsky, D. and W. Wittenberg (2006), “Interpretation of Regressions with Multiple Proxies,” *Review of Economic Studies*, 88(3), 549-562.

Mankiw, N. G., D. Romer, and D. Weil (1992), “A Contribution to the Empirics of Economic Growth,” *Quarterly Journal of Economics*, 107, 407-437.

Masanjala, W. and C. Papageorgiou (2004), “The Solow Model with CES Technology: Nonlinearities and Parameter Heterogeneity,” *Journal of Applied Econometrics*, 19, 2, 171-202.

Rajan, R. G. and A. Subramanian (2005a), “Aid and Growth: What Does the Cross-Country Evidence Really Show?” NBER Working Paper No. 11513.

Rajan, R. G. and A. Subramanian (2005b), “What Undermines Aid's Impact on Growth?” NBER Working Paper No. 11657.

Rodrik, D., A. Subramanian, and F. Trebbi (2004), “Institutions Rule: The Primacy of Institutions Over Geography and Integration in Economic Development,” *Journal of Economic Growth*, 9(2), 131-165.

Roodman, D. (2004), “The Anarchy of Numbers: Aid, Development, and Cross-country Empirics,” Center for Global Development Working Paper No. 32.

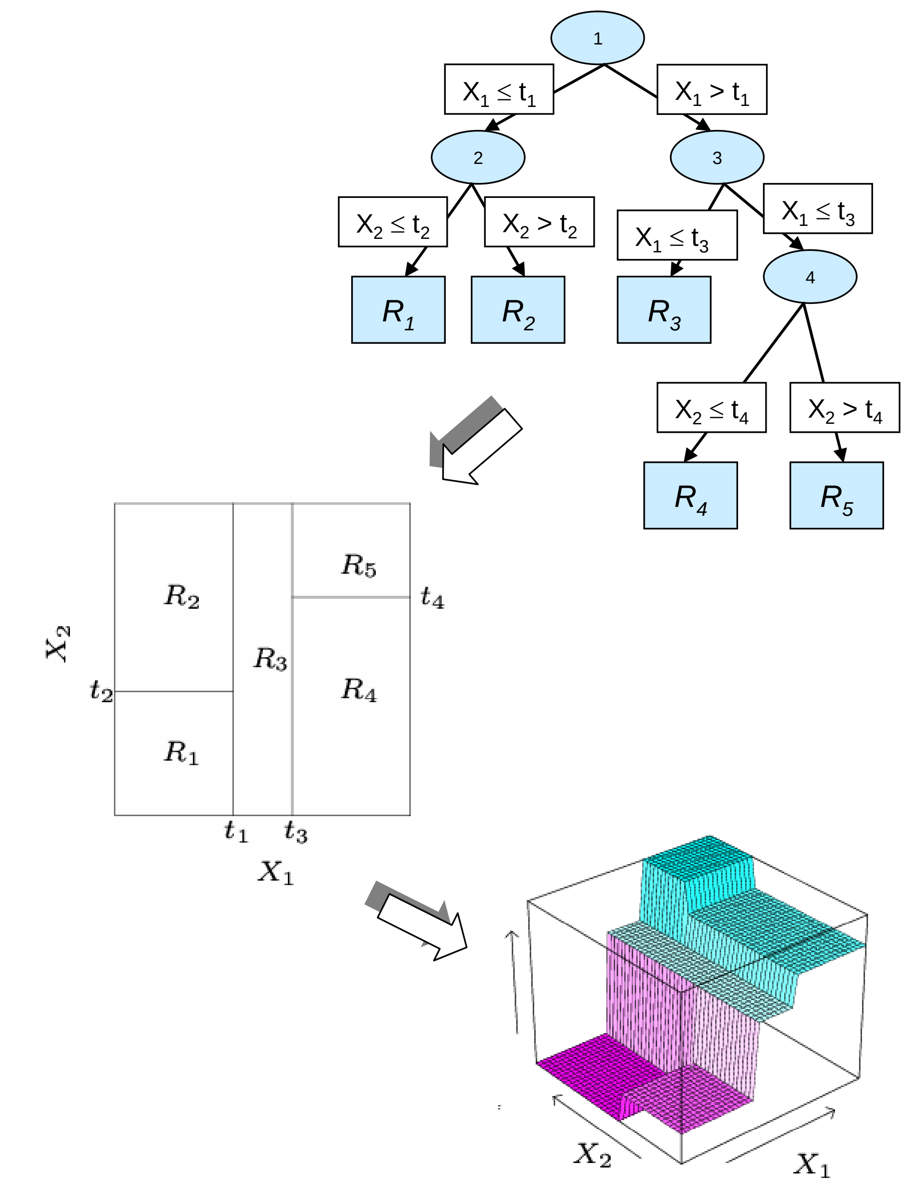
Sachs, J. D. and A. Warner (1995), “Economic Reform and the Process of Global Integration, *Brookings Papers on Economic Activity*, 1-118.

Sachs, J. D. (2003), “Institutions Don't Rule: Direct Effects of Geography on Per Capita Income,” NBER Working Paper No. 9490.

Sala-i-Martin, X., G. Doppelhofer, and R. Miller (2004), “Determinants of Long-term Growth: a Bayesian Averaging of Classical Estimates (BACE) Approach,” *American Economic Review*, 94, 4, 813-835.

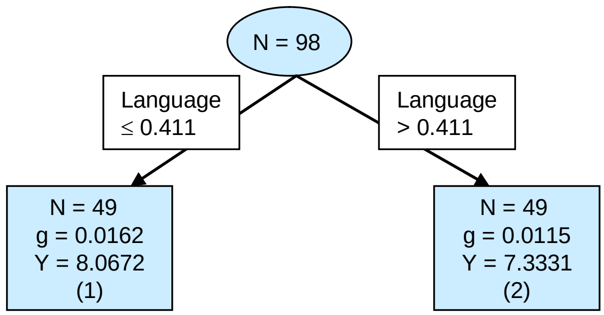
Tan, C. M., (2005), “No One True Path: Uncovering the Interplay between Geography, Institutions, and Fractionalization in Economic Development,” Tufts University, Dept. of Economics Working Paper No. 2005-12.

Figure 1*: Simple Tree Schematic



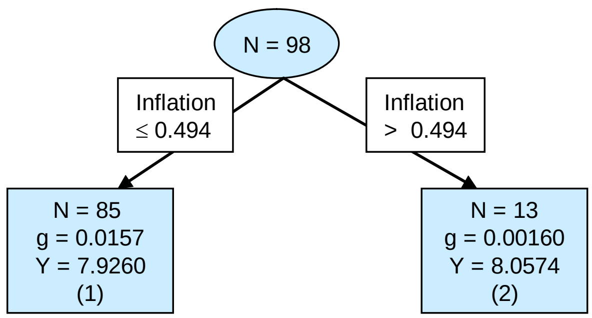
*Schematic due to Hastie, Tibshirani, and Friedman (2001).

Figure 2(a)*: Tree Diagram For BTREED Baseline Model



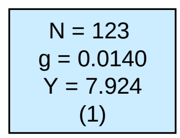
*Note that N gives the number of observations in each node, g stands for the average growth rate in real per capita GDP from 1965-94 for countries in the terminal node, and Y is the corresponding average level of log initial real per capita GDP in 1965.

Figure 2(b)*: Tree Diagram For BTREED Solow Model



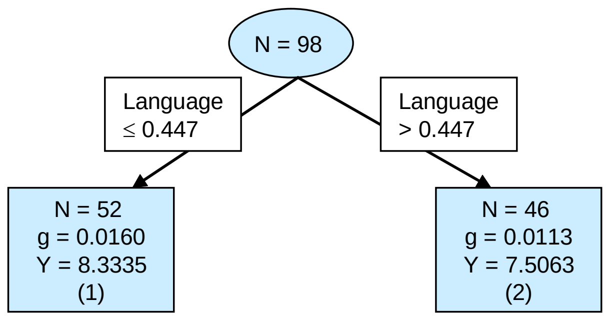
*Note that N gives the number of observations in each node, g stands for the average growth rate in real per capita GDP from 1965-94 for countries in the terminal node, and Y is the corresponding average level of log initial real per capita GDP in 1965.

Figure 2(c)*: Tree Diagram For BTREED Parsimonious Model



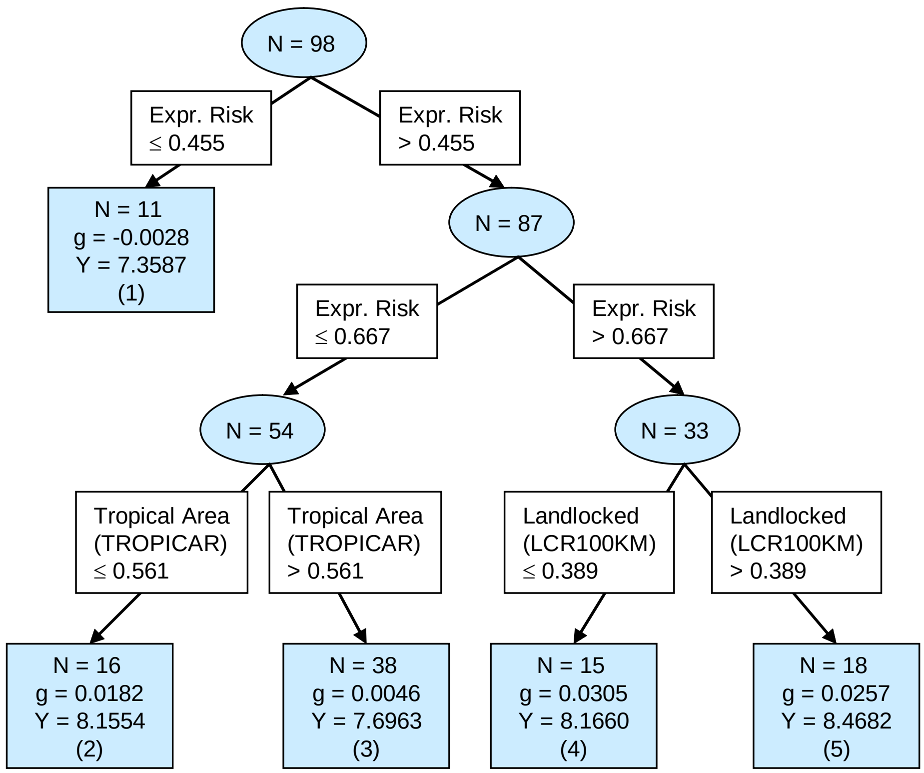
*Note that N gives the number of observations in each node, g stands for the average growth rate in real per capita GDP from 1965-94 for countries in the terminal node, and Y is the corresponding average level of log initial real per capita GDP in 1965.

Figure 3(a)*: Tree Diagram For TR Baseline Model



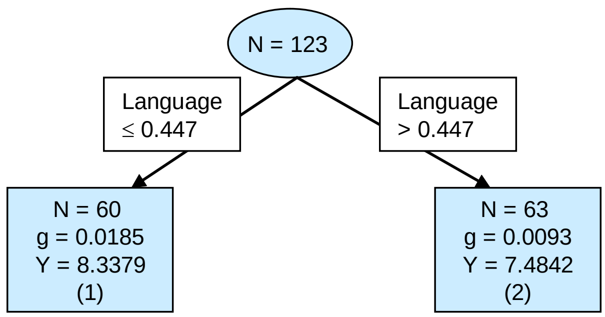
*Note that N gives the number of observations in each node, g stands for the average growth rate in real per capita GDP from 1965-94 for countries in the terminal node, and Y is the corresponding average level of log initial real per capita GDP in 1965.

Figure 3(b)*: Tree Diagram For TR Solow Model



*Note that N gives the number of observations in each node, g stands for the average growth rate in real per capita GDP from 1965-94 for countries in the terminal node, and Y is the corresponding average level of log initial real per capita GDP in 1965.

Figure 3(c)*: Tree Diagram For TR Parsimonious Model



*Note that N gives the number of observations in each node, g stands for the average growth rate in real per capita GDP from 1965-94 for countries in the terminal node, and Y is the corresponding average level of log initial real per capita GDP in 1965.

Figure 4(a): Hansen (2000) Confidence Intervals for Figure 3(a)

<u>First Split:</u>

Threshold Variable	Language
Threshold Estimate	0.44720000
95% Confidence Interval:	[0.411000, 0.458600]

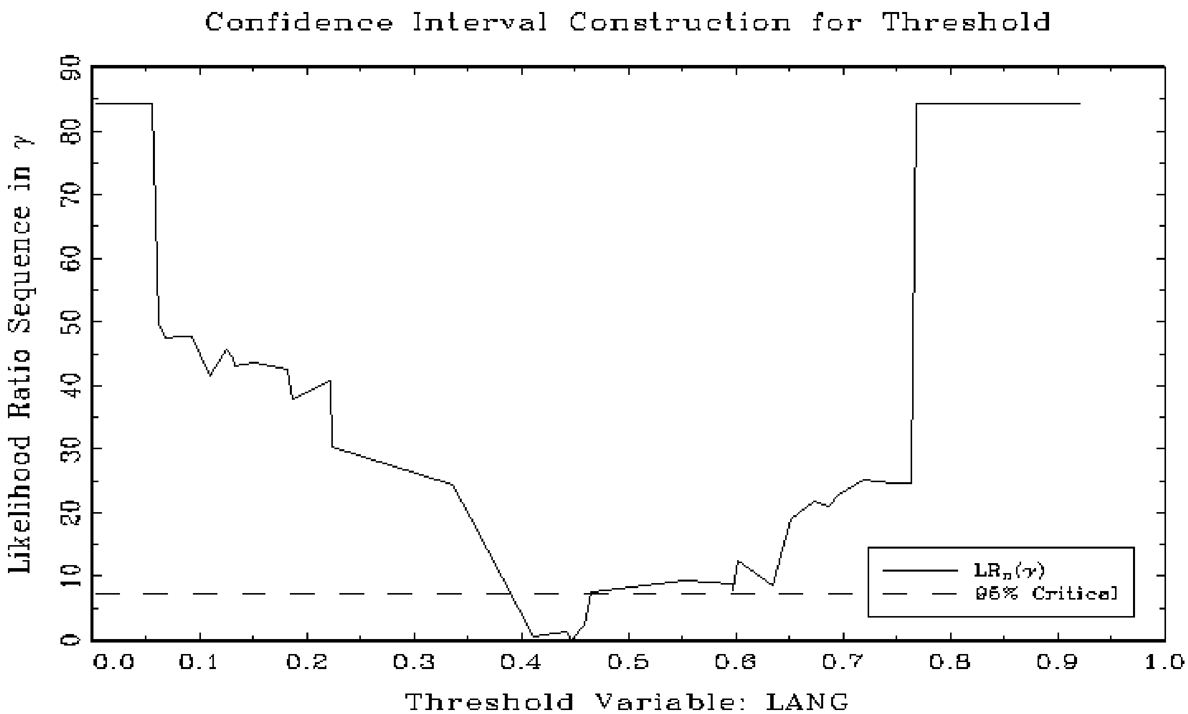
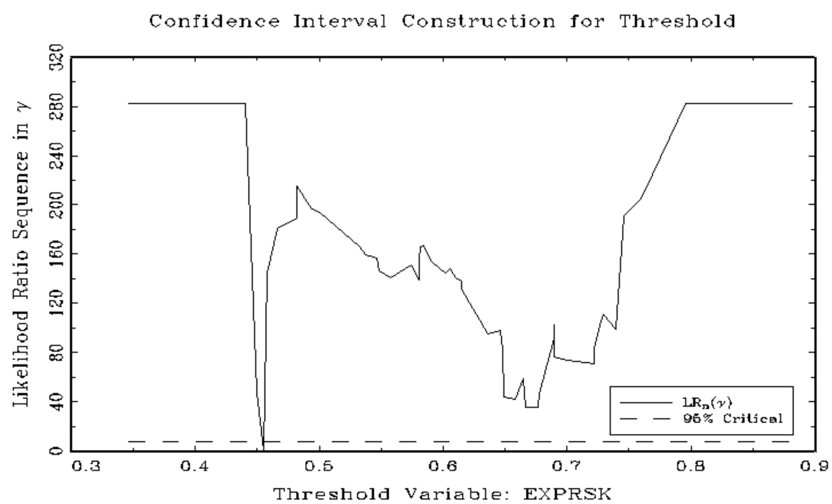


Figure 4(b): Hansen (2000) Confidence Intervals for Figure 3(b)

First Split

Threshold Variable	Expropriation Risk
Threshold Estimate	0.45538462
95% Confidence Interval:	[0.455384, 0.455384]



Second Split

Threshold Variable	Expropriation Risk
Threshold Estimate	0.66692308
95% Confidence Interval:	[0.649230, 0.677692]

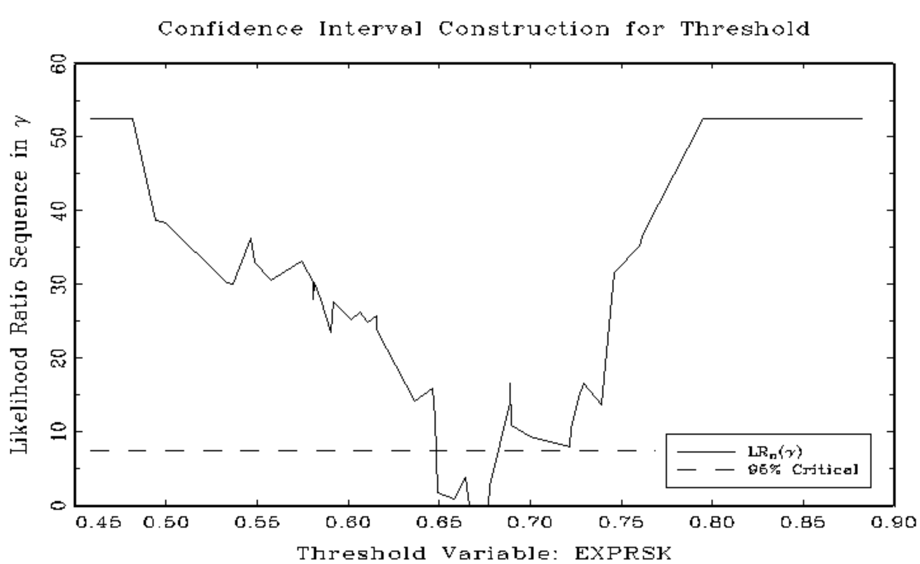
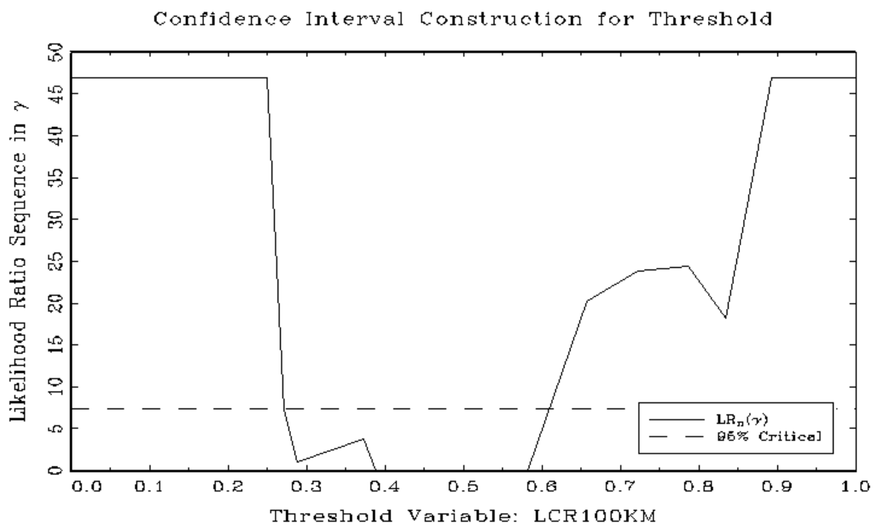


Figure 4(b) (cont.): Hansen (2000) Confidence Intervals for Figure 3(b)

<u>Third Split</u>

```
Threshold Variable            Landlocked (LCR100KM)
Threshold Estimate            0.38887620
95% Confidence Interval:      [0.270992, 0.582102]
```



<u>Fourth Split</u>

```
Threshold Variable            Tropical Area (TROPICAR)
Threshold Estimate            0.56140000
95% Confidence Interval:      [0.561400, 0.561400]
```

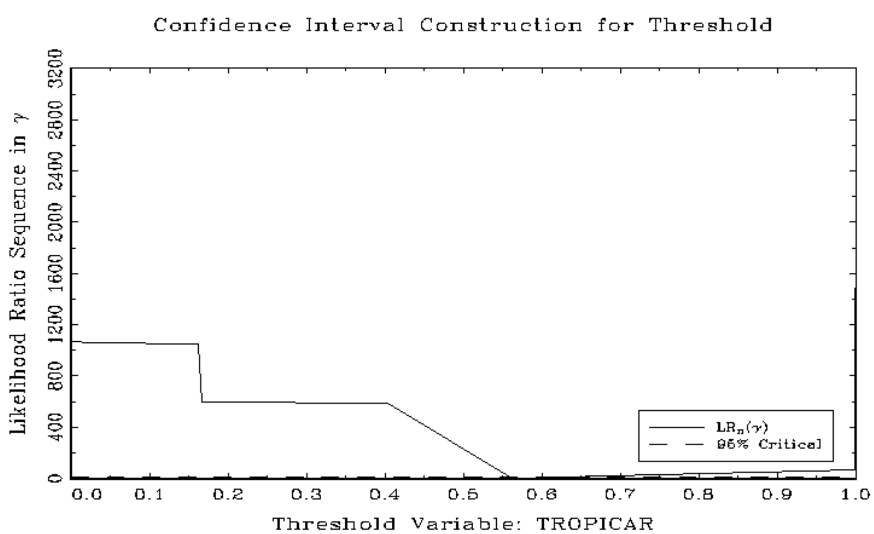


Figure 4(c): Hansen (2000) Confidence Intervals for Figure 3(c)

<u>First Split:</u>

Threshold Variable	Language
Threshold Estimate	0.44720000
95% Confidence Interval:	[0.335800, 0.597500]

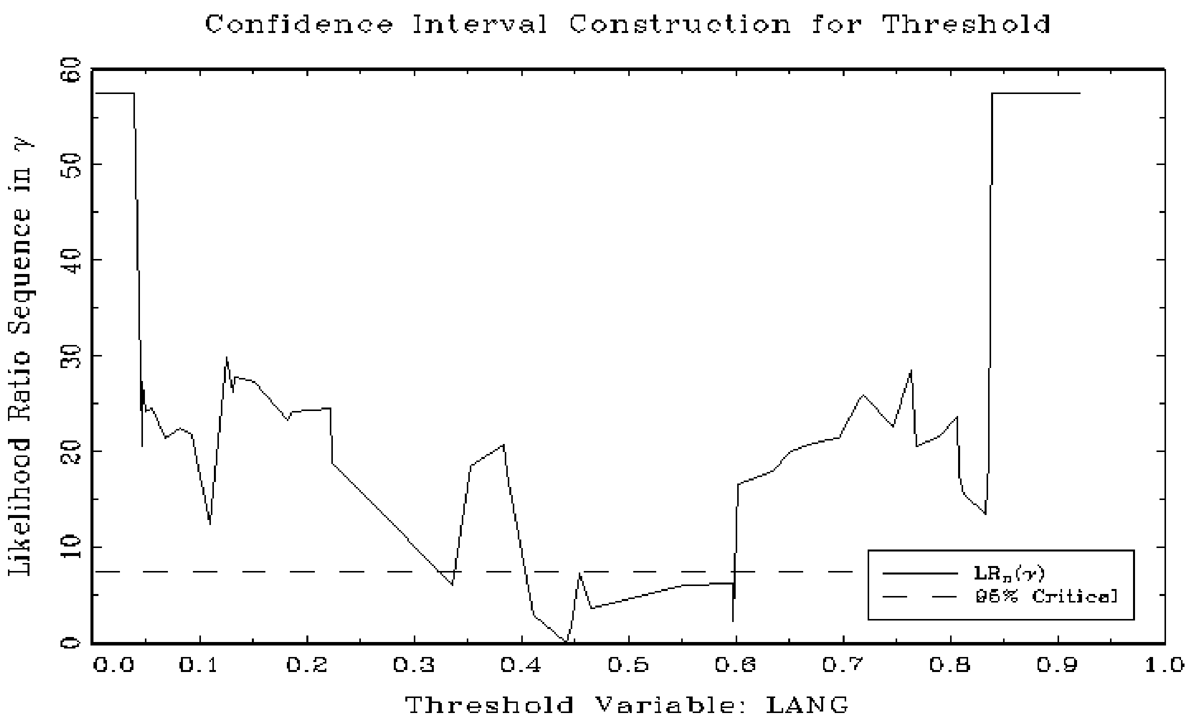
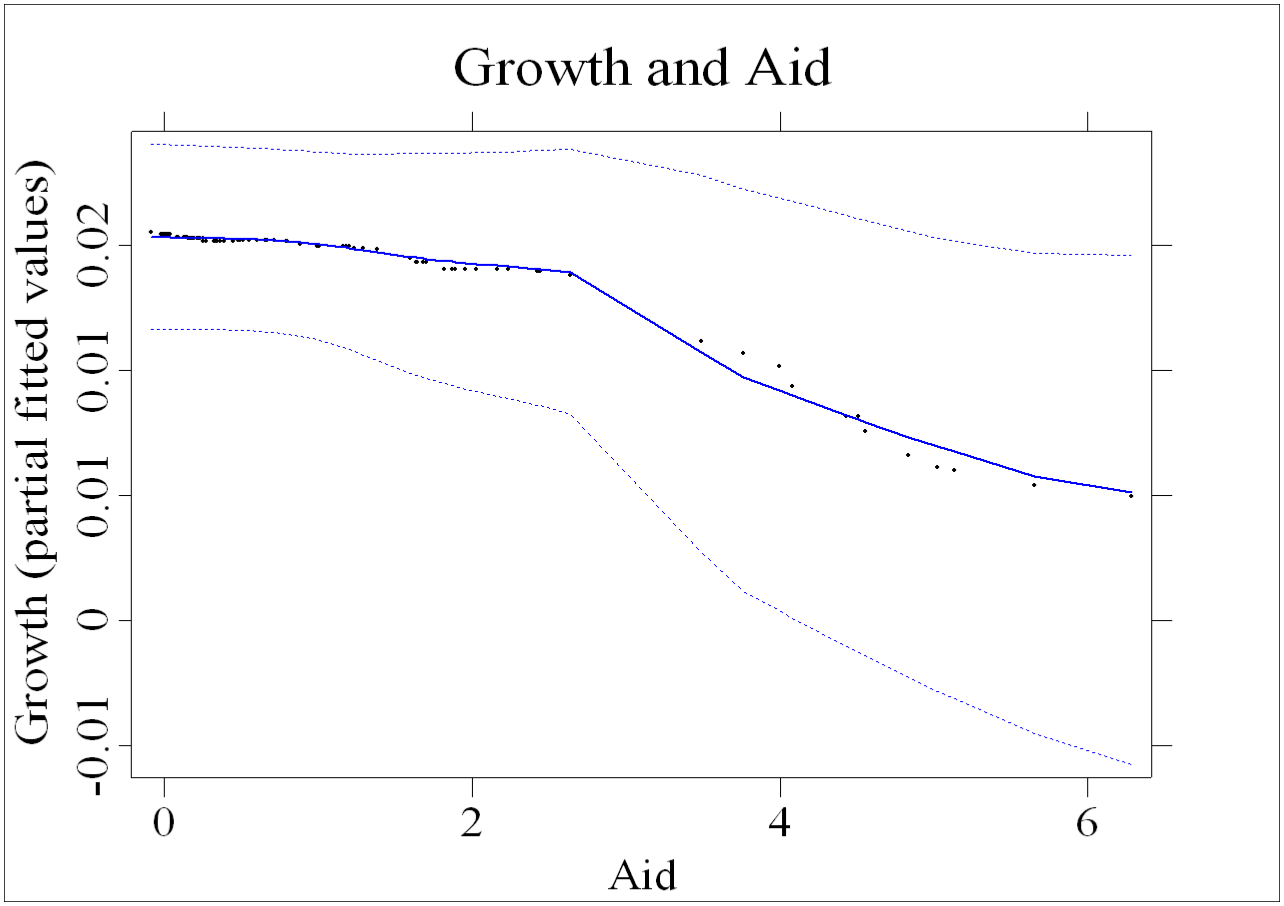
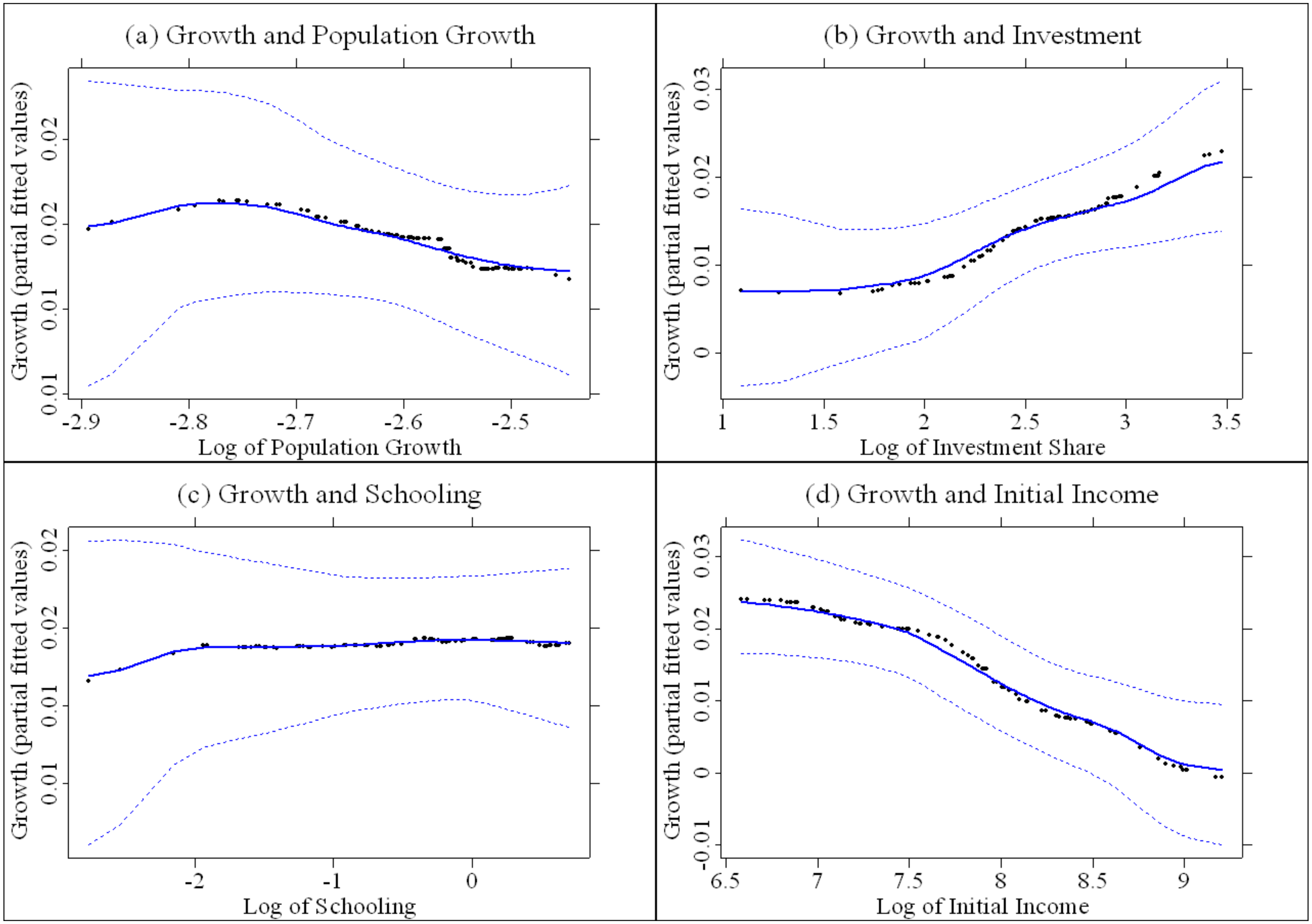


Figure 5(a): Partial Dependence Plot for Aid (Baseline/Solow[ϒ] Model)



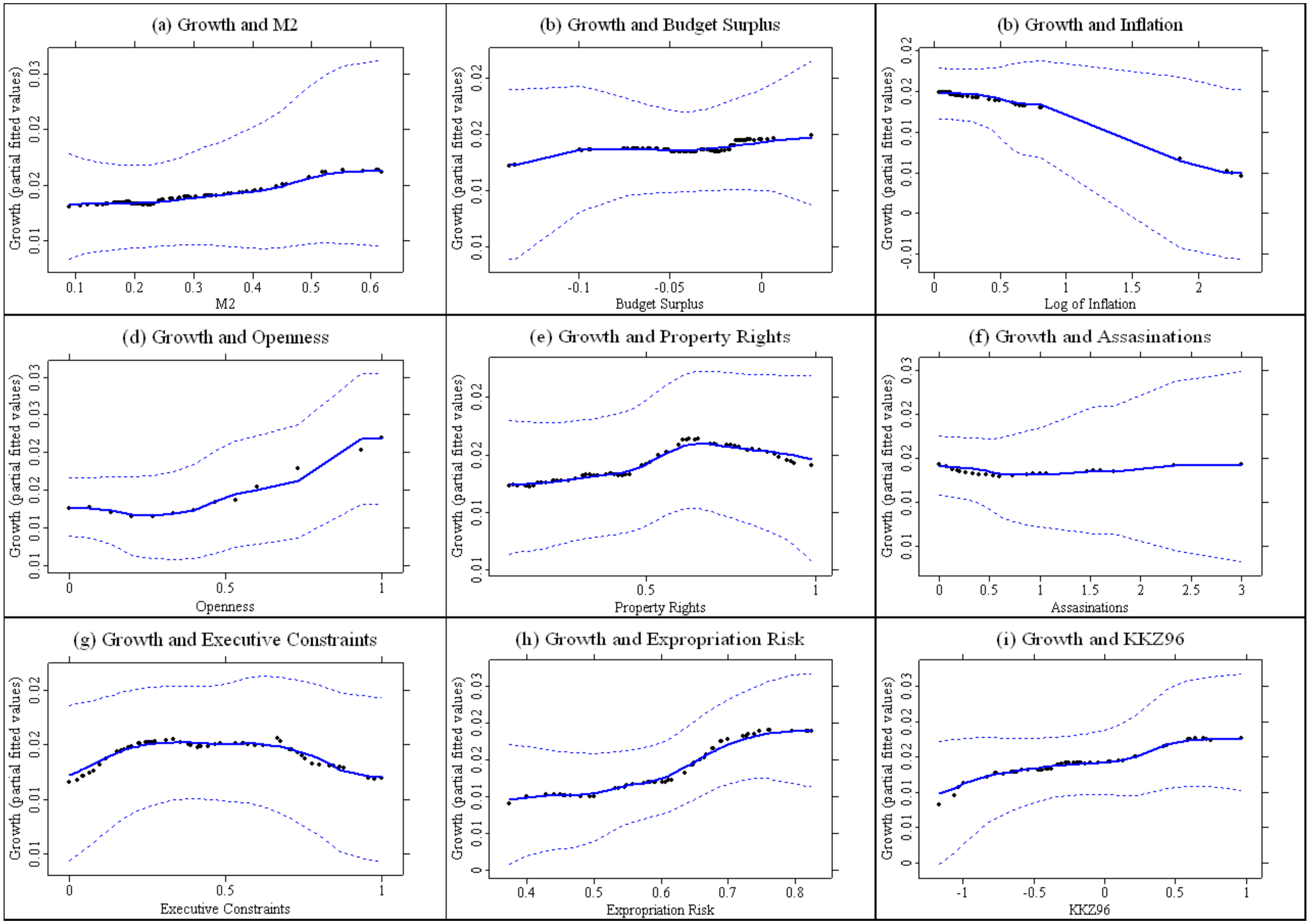
[ϒ] The BART partial dependence diagrams are the same for the Baseline and Solow Models (see Table 3 for model specifications) since both model specifications have the same set of variables.

Figure 5(b): Partial Dependence Plots for Solow Variables (Baseline/Solow[ϒ] Model)



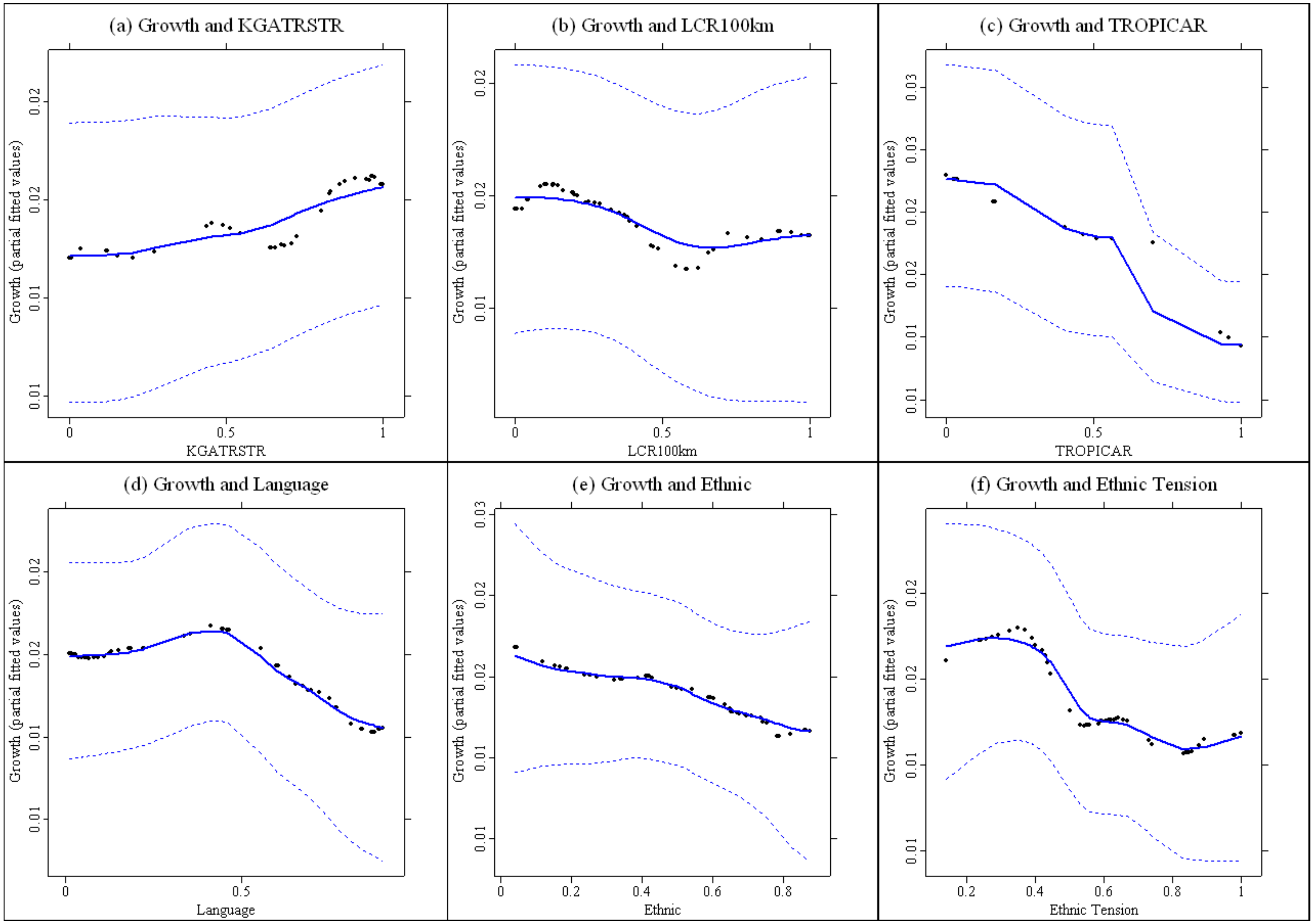
[ϒ] The BART partial dependence diagrams are the same for the Baseline and Solow Models (see Table 3 for model specifications) since both model specifications have the same set of variables.

Figure 5(c): Partial Dependence Plots for Macroeconomic Policy and Institutions (Baseline/Solow[ϒ] Model)



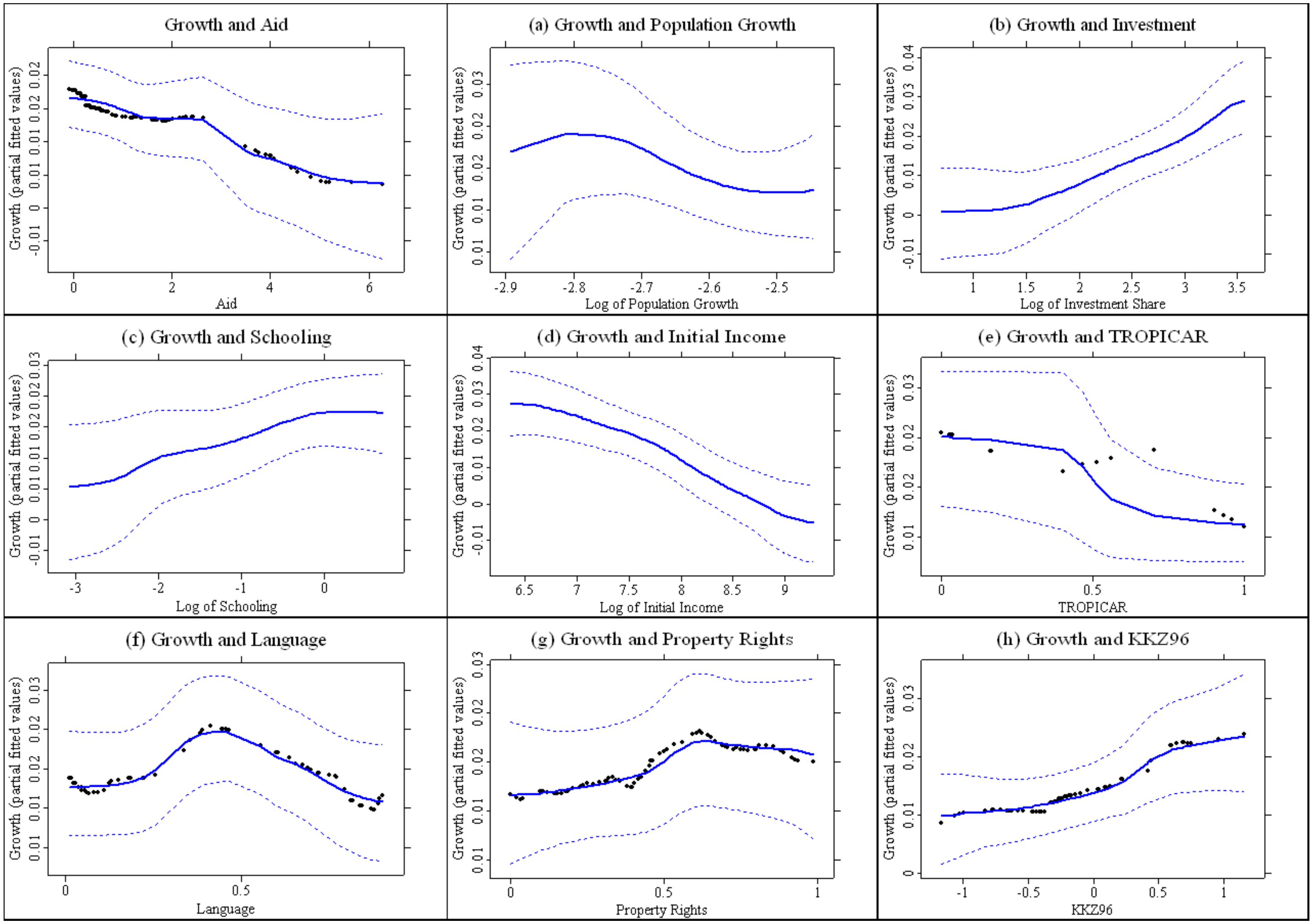
[ϒ] The BART partial dependence diagrams are the same for the Baseline and Solow Models (see Table 3 for model specifications) since both model specifications have the same set of variables.

Figure 5(d): Partial Dependence Plots for Other Fundamental Determinants (Baseline/Solow[Υ] Model)



[Υ] The BART partial dependence diagrams are the same for the Baseline and Solow Models (see Table 3 for model specifications) since both model specifications have the same set of variables.

Figure 6: Partial Dependence Plots (Parsimonious[ϒ] Model)



[ϒ] Please see Table 3 for model specification.

Table 1: Data Description

VARIABLE	DESCRIPTION	PANEL	SOURCE
Growth	GDP growth rates (using rgdpch)	1965-79, 1980-94	PWT61
Population Growth	logarithm of population growth + 0.05	1965-79, 1980-94	PWT61
Investment	logarithm of average investments/gdp	1965-79, 1980-94	PWT61
Schooling	logarithm of average years of male secondary and higher school attainment	1965, 1980	Barro-Lee(2000)
Initial Income	log of initial per capita income	1965, 1980	PWT61
KG Tropics	Percentage of land area classified as tropical and subtropical via the Koeppen-Geiger system.		CID, Harvard University
Landlocked (LCR100KM)	Percentage of a country's land area within 100km of an ice- free coast.		CID, Harvard University
Tropical Area (TROPICAR)	Fraction of land area in geographic tropics.		Gallup and Sachs, 1999
Language	Measure of linguistic fractionalization based on data describing shares of languages spoken as "mother tongues".		Alesina, A., A. Devleeschauwer, W. Easterly, S. Kurlat, and R. Wacziarg (2003)
Ethnic Fractionalization	Measure of ethnic fractionalization based on racial and linguistic characteristics.		Alesina, A., A. Devleeschauwer, W. Easterly, S. Kurlat, and R. Wacziarg (2003)
Ethnic Tension	This variable, which has been transformed to lie between 0 to 1, "measures the degree of tension within a country attributable to racial, nationality, or language divisions." Higher values correspond to lower degrees of ethnic tension. We take the average value of Ethnic Tension for the available data (1982-94) and repeat in each period.	1982-1994	International Country Risk Guide
Political Rights	Political Rights. The variable was tranformed using (7-x)/6 so that lower ratings (closer to zero) are given to countries with poor political rights and higher ratings (closer to one) are given to countries with better political rights.	1972-79, 1980-94	Freedom House 2005

Table 1 (cont.): Data Description

VARIABLE	DESCRIPTION	PANEL	SOURCE
Assassinations	Assassinations per capita	1965-79, 1980-94	Banks (2002)
Executive Constraints	Rescaled, from 0 to 1, with a higher score indicating more constraint: 0 indicates unlimited authority; score of 1 indicates executive parity or subordination. We calculated the average for each period.	1965-79, 1980-94	Polity IV dataset
Expropriation Risk	Risk of “outright confiscation and forced nationalization" of property. Rescaled, from 0 to 1, with a higher score indicating higher less risk of expropriation.	1982-94, 1982-94	IRIS
Governance (KKZ96)	Composite Governance index. It is calculated as the average of six variables: voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, rule of law, and control of corruption.	1996, 1996	Kaufmann, Kraay and Mastruzzi (2005)
Aid	Effective Development Assistance/ real GDP	1970-79, 1980-94	Roodman (2004)
Budget Surplus	Budget surplus	1965-79, 1980-94	Roodman (2004)
Inflation	ln(1+ inflation rate)	1965-79, 1980-94	Global Development Network Growth Database.
M2	Average Ratio of M2 to GDP	1965-79, 1980-94	Global Development Network Growth Database.
Openness	Average openness measure proposed by Sachs and Warner	1965-79, 1980-94	Sachs and Warner, 1995; Easterly et al., 2004; Wacziarg and Welch, 2002
East Asia	A dummy variable for East Asia		
Latin America & Caribbean	A dummy variable for Latin America		
Sub-Saharan Africa	A dummy variable for Sub-Saharan Africa		

Table 2: Summary Statistics

	Min.	Max.	Median	Mean	Std. Dev.
KG Tropics	0.000	1.000	0.656	0.547	0.400
Landlocked (LCR100KM)	0.000	1.000	0.363	0.433	0.349
Tropical Area (TROPICAR)	0.000	1.000	1.000	0.689	0.432
Language	0.003	0.923	0.427	0.418	0.320
Ethnic Fractionalization	0.039	0.930	0.540	0.507	0.235
Ethnic Tension	0.131	1.000	0.587	0.570	0.241
Political Rights	0.000	1.000	0.417	0.484	0.278
Assassinations	0.000	4.000	0.067	0.373	0.722
Executive Constraints	0.000	1.000	0.389	0.471	0.328
Expropriation Risk	0.346	0.883	0.613	0.614	0.120
Governance (KKZ96)	-1.869	1.159	-0.270	-0.195	0.589
East Asia	0.000	1.000	0.000	0.092	0.290
Sub-Saharan Africa	0.000	1.000	0.000	0.214	0.412
Latin America & Caribbean	0.000	1.000	0.000	0.245	0.432
M2	0.073	1.001	0.225	0.278	0.153
Budget Surplus	-0.206	0.092	-0.033	-0.039	0.040
Inflation	0.031	3.127	0.119	0.320	0.587
Openness	0.000	1.000	0.067	0.255	0.339
Aid	-0.328	9.482	0.495	1.316	1.823
Population Growth	-3.059	-2.365	-2.580	-2.602	0.111
Investment	0.698	3.563	2.568	2.501	0.520
Schooling	-4.017	1.226	-0.298	-0.489	0.936
Initial Income	6.094	9.344	7.906	7.843	0.742
Growth	-0.053	0.081	0.014	0.014	0.024

Table 3[◊]: Model Specifications

		Baseline Exercise		Solow Exercise		Parsimonious Exercise	
		Slope	Threshold	Slope	Threshold	Slope	Threshold
1	KG Tropics		X		X	-	-
2	Landlocked (LCR100KM)		X		X	-	-
3	Tropical Area (TROPICAR)	X	X		X	X	X
4	Language	X	X		X	X	X
5	Ethnic Fractionalization		X		X	-	-
6	Ethnic Tension		X		X	-	-
7	Political Rights		X		X	X	X
8	Assassinations	X	X		X	-	-
9	Executive Constraints		X		X	-	-
10	Expropriation Risk	X	X		X	-	-
11	Governance (KKZ96)		X		X	X	X
12	East Asia	X			X	X	
13	Sub-Saharan Africa	X			X	X	
14	Latin America & Caribbean	X			X	X	
15	M2	X	X		X	-	-
16	Budget Surplus	X	X		X	-	-
17	Inflation	X	X		X	-	-
18	Openness	X	X		X	-	-
19	Aid	X	X	X	X	X	X
20	Population Growth	X		X		X	
21	Investment	X		X		X	
22	Schooling	X		X		X	
23	Initial Income	X	X	X	X	X	X
24	Dummy 1980-94	X		X		X	
	Number of obs.	98		98		123	

◊ This Table describes the set of variables in the model space for each of the three specifications – Baseline, Solow, and Parsimonious. An "X" means that a variable was designated either to be a potential threshold variable, or a slope covariate (or, as the case may be, both). An "-" means that that variable was dropped from the model space.

Table 4[∇]: Country Breakdowns by Growth Regimes for BTREED and TR Models

	BTREED			TR		
Country	Baseline	Solow	Pars.	Baseline	Solow	Pars.
Africa						
Benin	-	-	1	-	-	2
Botswana	1	1	1	1[c]	4	1[c]
Cameroon	2	1	1	2	3	2
Central African Rep.	-	-	1	-	-	2
Congo, Rep.	2	1	1	2	1	2
Gambia	2	1	1	2	5	2
Ghana	2	1	1	2	3	2
Kenya	2	1	1	2	3	2
Lesotho	-	-	1	-	-	1
Malawi	2	1	1	2	3	2
Mali	2	1	1	2	1	2
Mauritius	-	-	1	-	-	2[c]
Mozambique	-	-	1	-	-	2
Niger	2	1	1	2	3	2
Senegal	2	1	1	2	3	2
Sierra Leone	2	1	1	2	3	2
South Africa	2	1	1	2	4	2
Togo	2	1	1	2	3	2
Uganda	2	2	1	2	1	2
Congo, Dem. Rep.	2	2	1	2	1	2
Zambia	2	2	1	2	3	2
Zimbabwe	2	1	1	1[c]	3	2[c]
Asia						
Bangladesh	1	1	1	1	2	1
China	1	1	1	1	4	1
India	2	1	1	2	4	2
Indonesia	2	1/2	1	2	5	2
Korea, Rep. of	1	1	1	1	5	1
Malaysia	2	1	1	2	5	2[c]
Nepal	-	-	1	-	-	2
Pakistan	2	1	1	2	2	2
Papua New Guinea	1	1	1	1	5	1[c]
Philippines	2	1	1	2	3	2
Singapore	-	-	1	-	-	1[c]
Sri Lanka	2	1	1	2	3	2[c]
Thailand	2	1	1	2[c]	4	2

[∇] A superscript "c" denotes countries within Hansen's 95% CI bound for the first threshold split as given in Figures 4(a)-(c). "1/2" indicates that a country was in one regime in one time period and another in the other.

Table 4▽ (cont.): Country Breakdowns by Growth Regimes for BTREED and TR Models

	BTREED			TR		
Country	Baseline	Solow	Pars.	Baseline	Solow	Pars.
Latin America & the Caribbean						
Argentina	1	2	1	1	2	1
Bolivia	1	1/2	1	1	3	1
Brazil	1	2	1	1	4	1
Chile	1	2	1	1	5	1
Colombia	1	1	1	1	4	1
Costa Rica	1	1	1	1	3	1
Dominican Republic	1	1	1	1	3	1
Ecuador	1	1	1	1	3	1
Guatemala	2	1	1	2[c]	1	2[c]
Honduras	1	1	1	1	3	1
Jamaica	1	1	1	1	3	1
Mexico	1	1	1	1	4	1
Nicaragua	1	2	1	1	1[c]	1
Panama	-	-	1	-	-	1[c]
Paraguay	2	1	1	2	2	2[c]
Peru	1	2	1	1	3	1[c]
Trinidad & Tobago	1	1	1	1	5	1
Uruguay	1	1	1	1	2	1
Venezuela	1	1	1	1	3	1
Europe, North Africa, & Middle East						
Algeria	2	1	1	1[c]	2	1[c]
Egypt, Arab Rep.	1	1	1	1	2	1
Hungary	1	1	1	1	5	1
Iran	2	1	1	2	1	2
Israel	2	2	1	2	5	2[c]
Jordan	1	1	1	1	2	1
Poland	1	2	1	1	5	1
Syrian Arab Rep.	1	1	1	1	2	1
Tunisia	1	1	1	1	2	1
Turkey	1	1	1	1	4	1

▽ A superscript "c" denotes countries within Hansen's 95% CI bound for the first threshold split as given in Figures 4(a)-(c). "1/2" indicates that a country was in one regime in one time period and another in the other.

Table 5+: BTREED Coefficient Estimates for Growth Regimes

	Baseline		*Solow*		*Parsimonious*
	(1)	*(2)*	*(1)*	*(2)*	*(1)*
Constant	0.1798***	-0.0160	-0.0027	-0.0660	0.1329**
	(0.0559)	(0.0848)	(0.0499)	(0.4004)	(0.0555)
Dummy 1980-94	-0.0117*	-0.0022	-0.0134	-0.0338	-0.0089**
	(0.0061)	(0.0046)	(0.0039)	(0.0249)	(0.0039)
Tropical Area	-0.0151***	-0.0155**	-	-	-0.0084**
(TROPICAR)	(0.0051)	(0.0064)	-	-	(0.0040)
Language	0.0004	-0.0003	-	-	-0.0010
	(0.0184)	(0.0123)	-	-	(0.0067)
Political Rights	-	-	-	-	0.0084
	-	-	-	-	(0.0065)
Assassinations	0.0019	-0.0011	-	-	-
	(0.0026)	(0.0024)	-	-	-
Expropriation	0.0735***	0.0271*	-	-	-
Risk	(0.0238)	(0.0155)	-	-	-
Governance	-	-	-	-	0.0128***
(KKZ96)	-	-	-	-	(0.0033)
East Asia	-0.0062	0.0129**	-	-	0.0115*
	(0.0081)	(0.0055)	-	-	(0.0059)
Sub-Saharan	0.0078	0.0155***	-	-	0.0039
Africa	(0.0059)	(0.0051)	-	-	(0.0044)
Latin America &	-0.0020	0.0487***	-	-	0.0068
Caribbean	(0.0057)	(0.0070)	-	-	(0.0047)
M2	0.0042	-0.0072	-	-	-
	(0.0192)	(0.0205)	-	-	-
Budget Surplus	0.1509**	-0.0887**	-	-	-
	(0.0621)	(0.0424)	-	-	-
Inflation	0.0007	-0.0118***	-	-	-
	(0.0042)	(0.0035)	-	-	-
Openness	0.0069	0.0227***	-	-	-
	(0.0077)	(0.0068)	-	-	-
Aid	-0.0022	-0.0045***	-0.0009	-0.0035	-0.0027**
	(0.0017)	(0.0013)	(0.0011)	(0.0088)	(0.0011)
Population	-0.0008	-0.0486*	-0.0392**	-0.0672	-0.0019
Growth	(0.0199)	(0.0280)	(0.0177)	(0.1438)	(0.0184)
Investment	0.0072	0.0150***	0.0260***	-0.0172	0.0173***
	(0.0083)	(0.0036)	(0.0037)	(0.0405)	(0.0030)
Schooling	-0.0018	0.0078***	0.0082***	0.0117	0.0061***
	(0.0047)	(0.0025)	(0.0024)	(0.0253)	(0.0022)
Initial Income	-0.0260***	-0.0181***	-0.0174***	-0.0045	-0.0198***
	(0.0039)	(0.0032)	(0.0030)	(0.0344)	(0.0029)
Number of obs.	49	49	85	13	123

+ Dependent variable is the growth rate of real GDP per capita across, respectively, the periods 1965-79 and 1980-94. Standard errors are in parentheses. Model specifications are described in Table 3. "***" indicates significance at the 1% level while "**" indicates significance at the 5% level and "*" at the 10% level.

Table 6[+]: TR Coefficient Estimates for Growth Regimes

	Baseline		Solow				
	(1)	*(2)*	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Constant	0.1858***	-0.0421	-2.2178***	0.1827***	0.1292*	-0.0084	0.1559***
	(0.0451)	(0.0572)	(0.1590)	(0.0247)	(0.0720)	(0.1940)	(0.0500)
Dummy 1980-94	-0.0109**	-0.0038	-0.0533***	-0.0157***	-0.0079*	-0.0157***	-0.0049
	(0.0052)	(0.0030)	(0.0069)	(0.0033)	(0.0043)	(0.0039)	(0.0047)
Tropical Area (TROPICAR)	-0.0151***	-0.0169***	-	-	-	-	-
	(0.0041)	(0.0049)	-	-	-	-	-
Language	-0.0052	0.0060	-	-	-	-	-
	(0.0099)	(0.0122)	-	-	-	-	-
Political Rights	-	-	-	-	-	-	-
	-	-	-	-	-	-	-
Assassinations	0.0015	-0.0004	-	-	-	-	-
	(0.0013)	(0.0014)	-	-	-	-	-
Expropriation Risk	0.0759***	0.0238**	-	-	-	-	-
	(0.0184)	(0.0093)	-	-	-	-	-
Governance (KKZ96)	-	-	-	-	-	-	-
	-	-	-	-	-	-	-
East Asia	-0.0064	0.0147***	-	-	-	-	-
	(0.0068)	(0.0048)	-	-	-	-	-
Sub-Saharan Africa	0.0079	0.0149***	-	-	-	-	-
	(0.0049)	(0.0041)	-	-	-	-	-
Latin America & Caribbean	-0.0012	0.0494***	-	-	-	-	-
	(0.0050)	(0.0062)	-	-	-	-	-
M2	-0.0035	0.0032	-	-	-	-	-
	(0.0154)	(0.0164)	-	-	-	-	-
Budget Surplus	0.1494***	-0.0877***	-	-	-	-	-
	(0.0445)	(0.0285)	-	-	-	-	-
Inflation	0.0001	-0.0117***	-	-	-	-	-
	(0.0030)	(0.0021)	-	-	-	-	-
Openness	0.0061	0.0250***	-	-	-	-	-
	(0.0048)	(0.0061)	-	-	-	-	-
Aid	-0.0016	-0.0040***	-0.0067***	-0.0015**	-0.0072***	0.0155***	-0.0068***
	(0.0013)	(0.0009)	(0.0016)	(0.0006)	(0.0017)	(0.0036)	(0.0008)
Population Growth	-0.0003	-0.0581***	-1.0114***	0.0090	-0.0120	-0.0400	0.0280
	(0.0157)	(0.0187)	(0.0888)	(0.0090)	(0.0262)	(0.0676)	(0.0201)
Investment	0.0069	0.0128***	0.0132	-0.0253***	0.0171***	0.0347***	0.0346***
	(0.0071)	(0.0027)	(0.0086)	(0.0058)	(0.0030)	(0.0082)	(0.0040)
Schooling	-0.0006	0.0075***	0.0280***	0.0037	0.0042**	0.0198***	-0.0036
	(0.0030)	(0.0020)	(0.0071)	(0.0045)	(0.0019)	(0.0060)	(0.0039)
Initial Income	-0.0264***	-0.0179***	-0.0422***	-0.0079***	-0.0233***	-0.0192***	-0.0166***
	(0.0027)	(0.0021)	(0.0096)	(0.0025)	(0.0029)	(0.0044)	(0.0050)
Number of obs.	52	46	11	16	38	15	18

[+] Dependent variable is the growth rate of real GDP per capita across, respectively, the periods 1965-79 and 1980-94. Standard errors are in parentheses. Model specifications are described in Table 3. "***" indicates significance at the 1% level while "**" indicates significance at the 5% level and "*" at the 10% level.

Table 6+ (cont.): TR Coefficient Estimates for Growth Regimes

	Parsimonious	
	(1)	*(2)*
Constant	0.1811***	-0.0307
	(0.0652)	(0.0662)
Dummy 1980-94	-0.0099**	-0.0069
	(0.0047)	(0.0046)
Tropical Area (TROPICAR)	-0.0101**	-0.0036
	(0.0042)	(0.0048)
Language	0.0140	0.0192
	(0.0117)	(0.0163)
Political Rights	0.0097	0.0052
	(0.0081)	(0.0085)
Assassinations	-	-
	-	-
Expropriation Risk	-	-
	-	-
Governance (KKZ96)	0.0158***	0.0098**
	(0.0032)	(0.0045)
East Asia	0.0010	0.0089*
	(0.0046)	(0.0051)
Sub-Saharan Africa	-0.0014	0.0028
	(0.0068)	(0.0049)
Latin America & Caribbean	-	-
	-	-
M2	-	-
	-	-
Budget Surplus	-	-
	-	-
Inflation	-	-
	-	-
Openness	-	-
	-	-
Aid	-0.0023	-0.0040***
	(0.0014)	(0.0013)
Population Growth	0.0089	-0.0666***
	(0.0187)	(0.0212)
Investment	0.0263***	0.0128***
	(0.0074)	(0.0034)
Schooling	0.0033	0.0073***
	(0.0032)	(0.0024)
Initial Income	-0.0250***	-0.0171***
	(0.0043)	(0.0035)
Number of obs.	60	63

+ Dependent variable is the growth rate of real GDP per capita across, respectively, the periods 1965-79 and 1980-94. White standard errors are in parentheses. Model specifications are described in Table 3. "***" indicates significance at the 1% level while "**" indicates significance at the 5% level and "*" at the 10% level.