THRESHOLDS AND CONTEXT DEPENDENCE IN GROWTH

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ABSTRACT

Is there a single recipe for fast growth? Much of the recent cross-section empirical growth literature implicitly assumes there is. Yet both development and growth theory — as well as casual empiricism — suggest pervasive non-linearities in the growth process. Low inflation may "grease the wheels of commerce" while high inflation may arrest them, secondary education may be crucial for promoting growth in open economies, but be largely ineffective in war-ravaged countries, etc. Such *threshold* effects and *context dependence* are difficult to capture in standard multivariate regressions, but are readily identified by classification tree analysis, undertaken here. Our results suggest that both types of non-linearities are indeed pervasive. The findings go some way towards explaining the limited robustness of cross-country growth regressions, and argue against the existence of a universal growth recipe.

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1 Introduction

What separates winners from losers in the great growth game? A decade of intensive research has identified a range of determinants influencing both rates of factor accumulation and disembodied technological progress. Yet to day no universal growth "recipe" has emerged from this literature: cross-sectional regressions continue to suffer from severe robustness problems [Levine and Renelt (1992)]. At the same time, the set of potential determinants found to be significant in some context or other continues to grow. Indeed, the empirical growth literature now arguably suffers from an embarrassment of riches, with proposed determinants of growth spanning a wide field including learning by doing [Arrow (1962)], education [Barro and Lee (1993a)], openness [Edwards (1992)], policy distortions [Easterly (1993)], inflation [Bruno and Easterly (1995)], fiscal policy [Barro (1990)], financial sector development [Greenwood and Jovanovic (1990)], income distribution [Perotti (1993)], R&D policies [Grossman and Helpman (1991)], natural resource endowments [Sachs and Warner (1995)], culture [Carroll, Rhee and Rhee (1994)], ethnic divisions [Easterly and Levine (1997)], democracy [Helliwell (1994)], equipment investment [DeLong and Summers (1991)], macro policies [Fischer (1993)], institutions [Knack and Keefer (1995)] and stock markets (Levine (1991)], among others.[1]

Faced with this plethora of causal factors, a number of recent studies have tried to pare the list to a core group of "essential" factors which separate the broad group of "winners" from "losers".[2] By and large, this work has maintained the methodological framework of cross-section regression analysis used in most of the empirical studies cited above. The research strategy has yielded useful insights, yet it has raised the bar quite high: with the exception of the investment ratio and, perhaps, trade openness, few variables appear to be robustly associated with growth.

Upon reflection, it is scarcely surprising that robust causal factors have proven so hard to find for the sixty to more than one hundred countries in the typical cross-country growth regressions. A substantial theoretical literature on nonlinear effects suggests precisely this absence of a strong link valid across a wide variety of countries. Specifically, there are good

[1] The size of the empirical growth literature prevents adequate referencing. The papers cited are intended as representative of the various sub branches of the literature.

[2] Levine and Renelt (1992), Barro and Lee (1993b), Sachs and Warner (1995).

reasons to suspect that the link between determinants and growth may be quite nonlinear, subject to both *threshold* effects and *complementarities.* Such non-linearities of course have a long tradition in the theoretical literature dating back to Young (1928), Rosenstein-Rodan's "big push" (1943,1963), Gerschenkron's (1962) "backwardness" hypothesis and Schumpeter's (1934) development theory. More recent work covering thresholds, path dependence and cross-dependence includes Clark (1987), Murphy, Shleifer and Vishny [1987], David (1988), Arthur (1989), Azariadis and Drazen [1990], Jones and Manuelli (1990), Kremer (1991), Aghion and Howitt (1992), Matsuyama (1992), Easterly (1994) and Ciccone and Matsuyama (1996), among others. Ex ante, the existence of such threshold effects is not implausible. For instance, it is hard to believe that raising the primary school enrollment rate from 90 to 95 percent has much effect on GDP growth. Yet arguably there is some threshold level of human capital below which GDP growth begins to suffer. Similarly, the effects of inflation on growth may be highly nonlinear, with a positive effect at very low inflation rates (as inflation "greases" the economy), and a negative effect at higher inflation rates (as inflation confuses relative price signals in the economy) [Bruno and Easterly (1996)].

More complex non-linearities enter to the extent that the effect of one growth determinant depends on the level, or presence, of another determinant. Thus, trivially, accumulation of human capital is unlikely to do much for a country ravaged by civil war. Similar, if less extreme, complementarities are likely to arise for many growth determinants. There is no reason to suppose, for instance, that the effect of inflation (or R&D expenditure) on GDP growth is independent of the level of physical or human capital in the country, the development of its financial system and the quality of property rights.

In the presence of such non-linearities, no universal growth recipe exists, rather, the elasticity of growth with respect to a particular factor will differ across countries dependent on their other characteristics. These differences are difficult to capture in the standard regression framework. By definition, the coefficients in a multi-variate regression analysis capture the marginal effect of a change in the explanatory variable, holding constant the other variables, impeding identification of threshold effects or complementarities. In principle, the problem can be overcome by including sufficiently many dummy variables and interactive terms in the regression. But in the absence of clear-cut theoretical predictions about the nature of the interaction, let alone the level of any thresholds, adding such terms soon becomes impractical given that the typical growth regression contains anywhere form eight to fifteen right hand side variables.

In this paper we adapt an alternative approach, abandoning the regression framework in favor of binary recursive tree estimation, a technique potentially well suited to identifying both threshold effects and cross-dependencies in a wide range of potential explanatory variables. Based on a sorting of countries into a fast- and a slow-growing group, the tree analysis searches across a set of potential explanatory variables to produce a sequence of criteria (in essence, a decision tree) which help determine the likelihood that a country will fall into each group. Since the sequence of criteria can depend upon previous branchings of the tree, the algorithm can readily accommodate cross-dependencies between the explanatory variables. The technique also establishes a *hierarchy* among the explanatory variables, based on their ability to discriminate between groups, thus providing a natural criterion for deciding which determinants belong in the "core" and which are of secondary importance. Finally, because the algorithm uses interior thresholds, it is by construction extremely robust to outliers, unlike regression analysis.

We construct trees for an annual data set of per capita GDP growth rates and a wide range of potential explanatory variables, covering all member countries of the International Monetary Fund over the period 1960-1996. We find, in line with most previous studies, that physical investment is the most important variable determining growth performance. Yet low investment does not condemn countries to low growth: high human capital and low inflation can partly compensate. Nor is high investment sufficient to generate high growth: high inflation renders rapid growth unlikely even in the presence of high investment. Investment, the key discriminant, is of course hardly an exogenous variable. Applying the methodology to countries ranked by their investment ratio reveals that openness of the economy is the key discriminant, with relative income, terms of trade variability and fiscal variables also having strong predictive power. Consistent with arguments made by Barro (1990), a striking non-linearity emerges with respect to the public sector share: both a very low, and a very high tax revenue to GDP ratio is associated with low investment.

The rest of the paper is organized as follows. Section 2 discusses binary recursive trees. Section 3 describes our data. Section 4 presents the main empirical results. Section 5 provides some brief concluding remarks.

2 Binary Recursive Trees

The empirical growth literature seeks to identify factors which are important in determining output growth. In the familiar cross-country regression framework (and likewise in limited dependent variables regressions if the dependent variable is "high" growth versus "low" growth), a variable is considered "important" if, controlling for the other regressors, it can explain a large fraction of the variation in the dependent variable. To be sure, this is a relevant gauge of the universal importance of a variable. Yet, even if a factor is not robustly linked to growth for the entire sample, it may well be of key importance for a subgroup of observations. This is more difficult to unearth within a regression framework, which implicitly assumes that the same functional form to apply to all countries.

For instance, human capital may be robustly associated with growth, but for the subgroup of countries suffering from military conflict, devoting more resources to education will arguably have a very limited effect. Standard regression analysis in effect computes an average of the effect over the two subsamples (war/no war), impeding identification of the link. If the type of non-linearity is known, controls can of course be included, in the above case, adding a dummy for civil conflict as well as the product of the dummy and the human capital accumulation variable would suffice to capture the effect. Yet such precise knowledge about the type of non-linearity is the exception rather than the rule. Without such priors, and in the presence of multiple explanatory variables, allowing for non-linearities in the standard regression framework soon becomes impractical, or requires imposing largely subjective ex-ante assumptions.

The presence of non-linearities can, however, be readily explored in the context of a sequential decision tree using criteria based on the explanatory variables (has the country experienced war? is per capita income in the lowest quintile?) at each node to split the sample into sub-branches. A binary recursive tree provides a specific algorithm for implementing this type of sequential decision tree. Formally, it is a sequence of rules for predicting a binary dependent variable y on the basis of a vector of independent variables x_j, $j = 1, ...J$. At each branch of the tree, the sample is split according to some threshold value $\hat{x}_j$ of one of the explanatory variables into two sub-branches. The splitting is repeated along the various sub-branches until a terminal node is reached.

To illustrate, suppose we sort all growth observation by size, and define the top third of observations as "high growth", coded as 1, and the bottom third as "low growth", coded as 0. The sample is then randomly separated into a core sample and a smaller test sample used for robustness checks. For the core sample, the algorithm searches for sequential splits, each consisting of the explanatory variable, and its associated threshold value, which best discriminates between the two groups. In most cases, the fit will not be perfect. Suppose, for example, that investment is correlated with growth, and is thus a potentially useful discriminant. There will, however, be some countries that have high investment rates but (nonetheless) belong to the low growth sample (a type I error), and others that have low investment rates but belong to the high growth sample (a type II error). The algorithm searches over all observed values of the investment rate until it finds the threshold value $\hat{x}_j$ which minimizes the sum of the type I and type II errors.[3]

This minimum sum of errors provides a natural gauge of the ability of investment rates to predict fast versus slow GDP growth. The same procedure is applied sequentially to *each* of the J explanatory variables (e.g. human capital, trade openness, etc). Sorting all explanatory variables by their minimum error then provides a ranking of their relative ability to discriminate between the two groups. To check robustness, the threshold for each variable (computed for the core sample) is then used to split the test sample, yielding a second sum of errors. Together, the core sample and the test sample scores provide an overall measure of the ability of the variable to discriminate. The variable with the smallest error (with the associated best threshold) is then used to form the first node. All sample observations exceeding the threshold are sorted into one sub-branch, the remaining observations are sorted into the second sub-branch.

For each sub-branch, the algorithm is then repeated. In principle, this process could continue until every observation has been placed into its own branch. This would be akin to including as many explanatory variables as observations in a regression and thus getting a "perfect," if meaningless, fit. A termination rule is thus required. The rule used resembles, loosely speaking, an *adjusted* R^2 criterion. After each split, the improvement in the overall fit (which, just like the change in the raw R^2 upon adding an additional explanatory variable is always non-negative) is combined with a penalty on the number of branches which promotes parsimony. If the penalty exceeds the improvement, the branch

[3]Depending upon the question examined, different weights can be attached to type I versus type II errors. For the present application, both types were weighted equally.

is terminated at the prior node, if not, the algorithm continues.

Several aspects of the algorithm are noteworthy. First, the algorithm automatically establishes both a global (full sample) and a set of local (sub-sample) priority ordering among the potential determinants. It thus identifies both globally important variables and variables which, while not globally important, are nevertheless significant for a sizable subset of observations. Second, it allows for a variable to only become an important determinant conditional on a number of prior condition on other variables having been met, and thus automatically allows for context dependence. Third, the procedure is very robust to outliers since splits occur on an interior threshold, an issue of particular importance in our application (see Levine and Renelt [1992]).[4] Fourth, the decision tree is invariant to *any* monotone transformation of the variables. This is especially useful in the empirical growth literature, where there is very little theory to provide guidance on the appropriate functional form.

3 Data

We use an annual data set covering all IMF member countries for which data are available over the period 1960-1996. The data are taken from the IMF's World Economic Outlook and International Finance Statistics databases.[5] The starting sample comprises 2,181 growth observations for 107 countries. We first sort this data set, according to the per capita GDP growth rates, into three equal-sized groups. Observations in the top one-third are classified as "high growth" (corresponding to average per capita growth rates of 6 percent per year), and observations in the bottom third are classified as low growth (corresponding to average per capita growth rates of -2.5 percent per year); the middle one-third observations are dropped, yielding 1,454 observations in the data set used for the analysis.[6]

Growth can arise from the accumulation of inputs and from disembodied productivity

[4] The difference to regression analysis arises from the implicit weighting scheme: while the squared residual regression criterion of fit depends upon the size of the "miss", the binary tree does not. In consequence, the overall score of the tree will rarely be enhanced by adding a separate node to capture a single outlier.

[5] With the exception of the Business Environmental Risk Intelligence (BERI) data on institutional characteristics (indicators of the degree of bureaucratic delays, the enforceability of contracts, nationalization risk, and quality of communication and transportation infrastructure) which were kindly provided by the IRIS Center, University of Maryland, and the data on black market exchange rates (taken from Pick's Currency Yearbooks).

[6] We also consider other definitions of "high" versus "low" growth, these are described later.

improvements. On the accumulation side, we follow the usual practice of measuring the growth in physical capital by the investment to GDP ratio (I/Y). Human capital accumulation has been proxied by a variety of different variables in the empirical growth literature, including school enrollment rates, average years of primary and secondary education, life expectancy and student/teacher ratios. As these tend to be highly correlated, we use the first principal component of primary and secondary school enrollment rates and life expectancy as a measure of human capital (HK). To simplify interpretation of the variable, results are stated in terms of percentiles (e.g. human capital in the top 10^{th} percentile of observations).

To allow for conditional convergence effects across countries, we include the log of the ratio of US per capita income to country j's per capita income in 1960 (Y^{US}/Y). Fiscal effects are proxied by the ratios (to GDP) of revenues (τ/Y), public consumption (G/Y), and the fiscal balance (B/Y) [Barro (1990)]. As these ratios are endogeneous to current GDP growth, we use the average value of the ratios over the preceding three years. Openness effects are captured by the sample average of the ratio of exports plus imports to GDP, ($\frac{X+M}{Y}$) [Edwards (1992)]. The (log) of the black market exchange rate premium (BLK) provides a measure of the overvaluation of the real exchange rate and, in at least some instances, of macroeconomic mismanagement more generally [Barro and Lee (1993b)]. The terms of trade volatility σ_{TT} , is used as a measure of the importance of external shocks. Finally, we include indicator variables for two cataclysmic events, drought ($DROUGHT$) and war fatalities ($DEATH$).

4 Empirical Results

To provide a comparison between binary recursive trees and more standard multivariate analysis, we begin by reporting the probit estimates (where the dependent variable equals unity for fast growth observations):

$$
\begin{array}{lcccc}
I_{\Delta y^{high}} = & 4.37 I/Y & -0.12\, log(\pi) & -18.9\Delta pop & -0.06 G/Y \\
 & (7.77) & (3.87) & (5.25) & (0.52) \\
 & -1.14 \tau/Y & +0.95\sigma_{TT} & +0.27\log(Y_{60}^{US}/Y_{60}) & +0.45\,(x+m)/Y \\
 & (2.71) & (2.82) & (4.17) & (1.74) \\
 & +\,0.58 B/Y & -0.26\, log(Blk) & +\,0.026 HK & -0.15\, DEATH \\
 & (0.84) & (2.97) & (4.02) & (1.29) \\
 & -0.54\, DROUGHT & & & \\
 & (5.68) & & &
\end{array}
\qquad (1)
$$

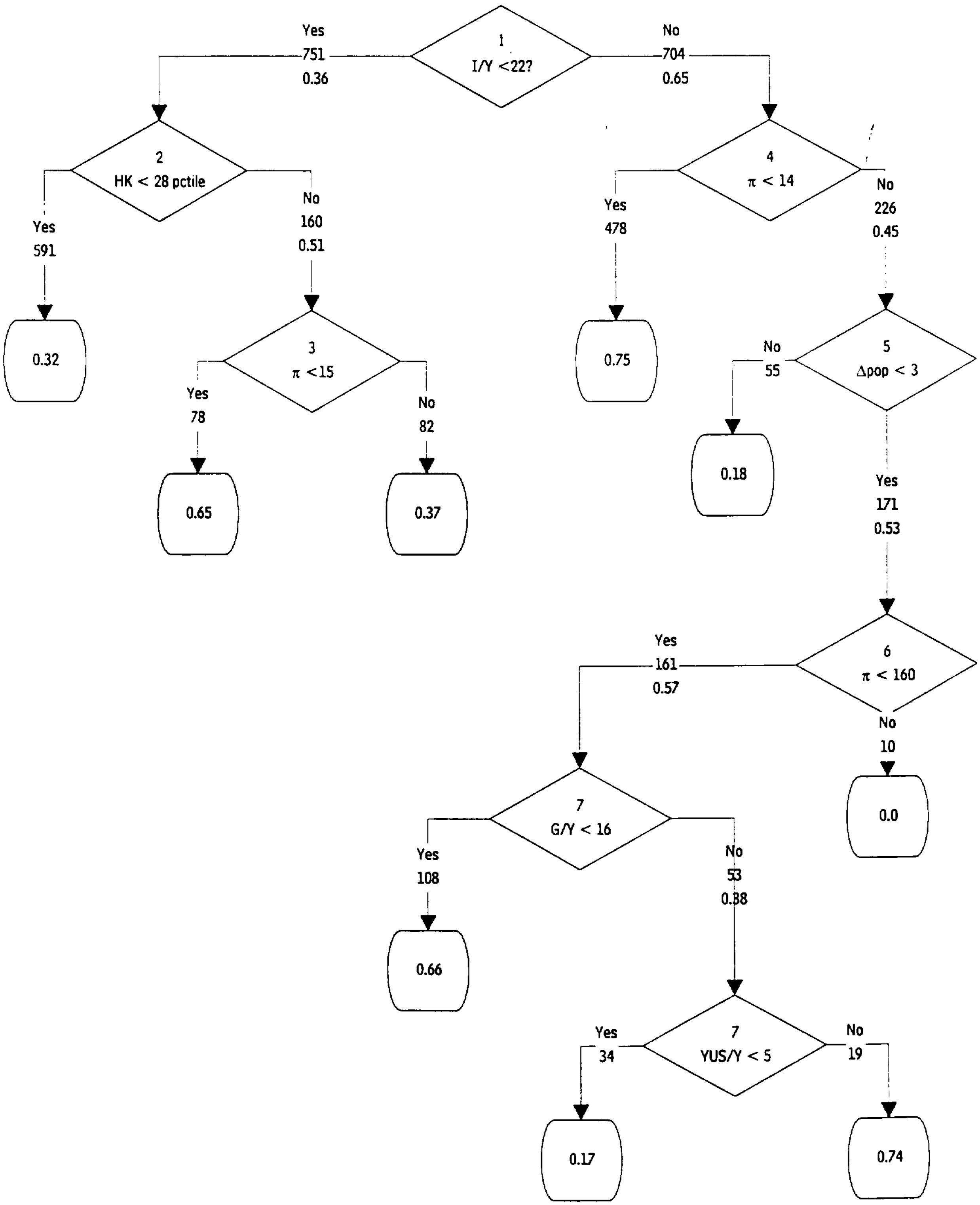
The probit (which predicts 68 percent of the observations correctly) identifies investment, inflation, population growth, human capital, and black market exchange rate premia (as well as the "catch-up" term, and drought or war conditions) as "significant" determinants of rapid economic growth. But it does not reveal whether, for example, the effects on inflation on growth depend upon the level of investment, or whether investment has any positive effect on growth in countries engaged at war. To address that type of question, we turn next to binary recursive trees.

The first tree, based on a classification of observations into the top-third versus the bottom-third growth rates, is depicted in figure 1. The overall quality of the rules embodied in the tree can be evaluated by their ability to divide the test sample into high and low growth observations. Seventy-five percent of the low growth observations and almost seventy percent of the high growth observations were correctly classified.[7]

The tree is based on 1,455 observations, half of which are high growth. The first branch of the tree splits on the investment ratio, with a threshold level of 22 percent of GDP. There are 751 observations for which the investment rate is below 22 percent, and the probability of high growth for these observations is 0.36. Conversely, there are 704 observations for which

[7] As there is an equal number of high and low growth observations, random allocation would, on average, have correctly classified half of the observations.

Figure 1: Determinants of high growth: top 1/3 obs vs. bottom 1/3 obs



All decision criteria in percent, unless otherwise stated

Figures in italics are the probability of high growth, conditional on being at the current node

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the investment rate exceeds 22 percent of GDP, and for these observations the probability of high growth is almost twice as high, at 0.65. This first split thus confirms the findings of prior studies (e.g. Renelt and Levine [1992], Barro (1991), Barro and Lee (1991b)) that high investment is strongly positively correlated with (though not a sufficient condition for) high growth. The finding raises the familiar question whether investment itself should be treated as an endogenous variable. To address this issue, below we report results for a binary tree for investment itself, using the 22 percent threshold to divide investment observations into "high" and "low" subsamples.

Returning to the growth tree, for countries with investment rates below 22 percent of GDP, the next most important discriminant is human capital. Node 2 shows that the 591 observations at or below the 28^{th} percentile in terms of human capital have a 0.32 probability of being in the high growth group (the probability is for the subsample, and thus conditional on having an investment ratio below 22 percent). In contrast, the 160 observations with human capital above the 28^{th} percentile threshold) have a probability of 0.51 of belonging to the high growth group.[8] Among these, a further distinction can be made between those with inflation rates above 15 percent per year (who have a 0.37 probability of high growth) and those with inflation rates below this threshold, who have a 0.65 probability of high growth. Summarizing this branch, among observations with relatively low investment ratios, the probability of belonging to the high growth group is boosted by the level of human capital, and particularly so if inflation is relatively low.

Turning to the second main branch — observations with investment ratios above 22 percent —, the most important variable distinguishing between high and low growth, is inflation. For this group, a inflation rate below fourteen percent raises the probability of belonging to the high growth group to seventy-five percent, contrasted with a forty-five percent probability for observations exceeding this threshold. Taking the latter group of high investment and high inflation countries, those with rapid population growth or hyperinflationary rates of inflation (node 6) have very small probabilities of attaining high

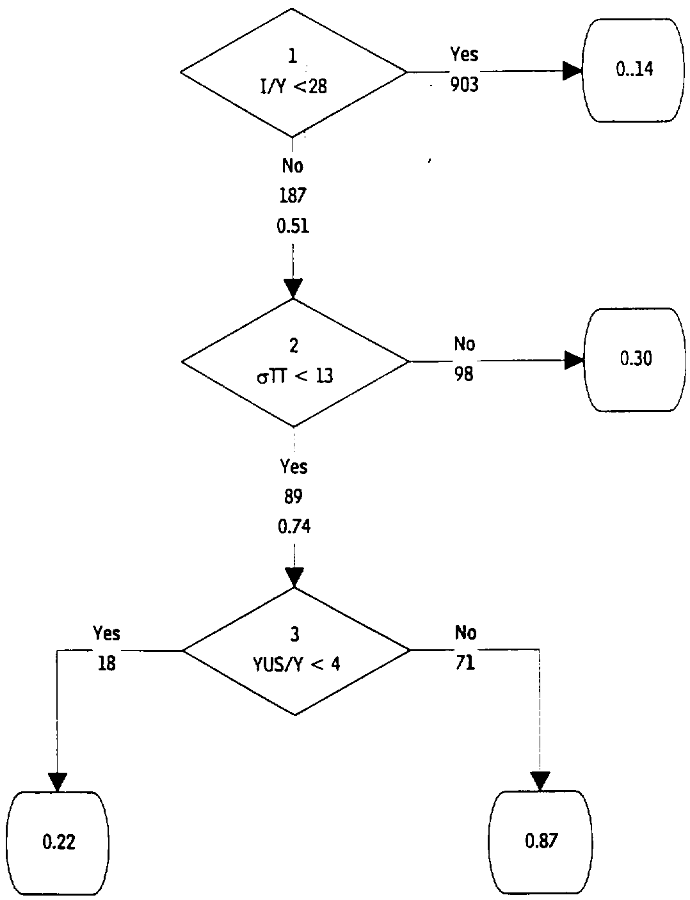
[8]It may seem odd that there are more than three times as many observations in the bottom three deciles of the human capital distribution as in the top seven deciles. The reason is however simple: the deciles are defined vis a vis the entire sample. As high human capital is strongly positively correlated with high investment ratios, most of the high human capital observations do not belong to this branch of the classification tree.

growth. Among the 161 observations characterized by high but not extreme inflation, high investment and moderate population growth, a larger shares of public sector activity (measured by the share of government consumption in output) is associated with a lower probability of rapid growth (a conditional probability of 0.38 compared to 0.66), among observations with sizable public sectors, initially relatively poorer countries fare better.

Viewed in its entirety, the growth tree suggests that threshold effects and cross- dependencies are in fact a feature of the data, a finding which may partly explain the lack of robustness of growth regressions [Renelt and Levine (1992)]. For instance, a higher level of human capital is only associated with a greater probability of high growth for countries with low investment rates. Similarly, the income catch-up term is only highly significant at node 7, that is, very poor countries also characterized by high investment, high inflation and moderate population growth. To the degree that these subsamples are sufficiently large relative to the total sample size, cross-section regressions will identify human capital and initial income as "significant" determinants of growth. Yet fairly small changes in the sample composition may have large effects on the significance of the estimated coefficients, even if a robust relation continues to hold for the subsample of low investment countries. The presence of such non-linearity may thus provide an explanation both for the continued expansion of the set of factors found to be "significant" in cross-country regressions, and for the lack of robustness in these regressions to changes in sample size.

The precise thresholds identified by the tree obviously depend on our definition of "high" versus "low" growth. But the variables chosen by the algorithm, and the general structure of the tree, are quite similar for other reasonable definitions of high and low growth. If 5-year averages of the data are used instead of annual data (to minimize the influence of business cycle fluctuations) the algorithm identifies population growth, the rate of investment, and the inflation rate as key determinants of rapid GDP growth. Defining "high" and "low" growth as above-median and as below-median growth (thus keeping the entire sample of 2181 observations) yields a tree for which a high investment ratio (indeed, with the same 22 percent threshold) raises the probability of high growth from 0.40 to 0.61, with subsequent splits on human capital (for low investment countries), and inflation for the high investment countries. If the focus is changed from "fast versus slow" to "extreme" (defined as observations in the top decile of the dataset) versus "moderate" (defined as observations in the 3rd to 7th decile) growth [Figure 2], the first node again depends upon

Figure 2: Top 10 percent vs Bottom 30-70 percent



All decision criteria in percent, unless otherwise stated

Figures in italics are the probability of high growth, conditional on being at the current node

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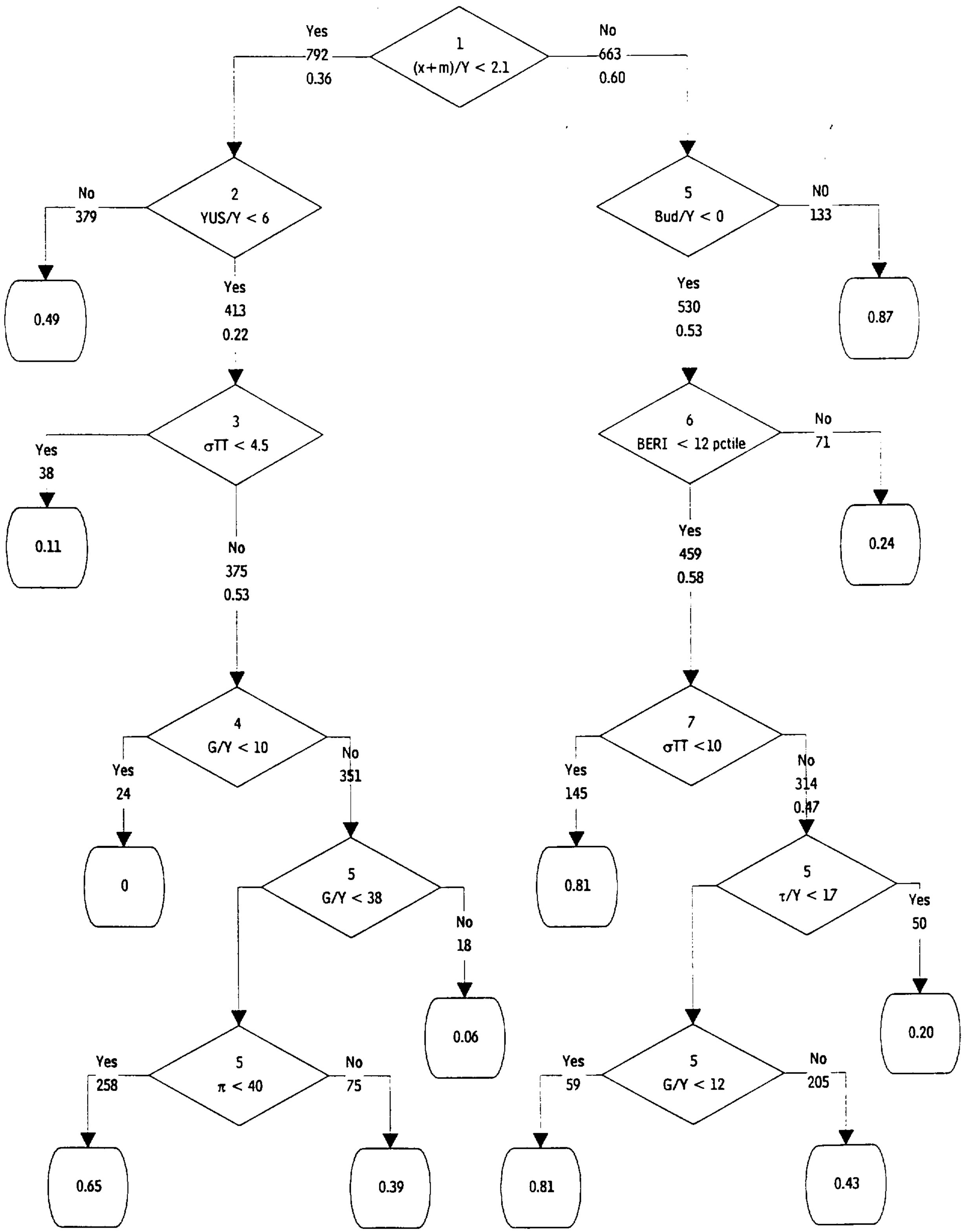
the investment rate, but with a threshold level of 28 percent of GDP (which raises the probability of high growth from 0.14 to 0.51). Subsequent nodes are split on the standard deviation of the terms of trade (with a low variability associated with a higher conditional probability of high growth) and on the income gap (again suggested convergence for a subgroup of observations).

While the precise thresholds vary somewhat across these trees, there is thus also substantial agreement: high investment is strongly associated with high growth, but is neither a sufficient, nor a necessary condition: high human capital and monetary stability can compensate for low investment, while high inflation can substantial reduce growth even with high investment.

Given these results, and considering the likely endogeneity of investment, it is of some interest to learn about the factors separating high investment from low investment observations. We define observations as "high investment" if they exceed the twenty-two percent threshold identified in the first growth tree, and as "low growth otherwise. Figure 3 presents the resulting tree.[9] The single most important discriminant turns out to be the openness of the economy: observations with trade ratios above 20 percent have almost twice the probability of high investment (0.60) than the remaining sample. Among the relatively closed sub-sample, richer countries tend to have low investment rates (node 2), as do, controlling for initial income, countries with high terms of trade variability. Nodes 4 and 5 reveal a marked two-sided threshold effect: both observations with very low tax revenues (possibly reflecting chaotic economic conditions) and observations with revenues shares above 40 percent of GDP (possibly reflecting distortionary tax rates) are unlikely to fall into the high investment group [Barro (1989)]. Finally, inflation rates above 40 percent are also associated with a much lower probability of falling into the high investment category. Turning to the more open observations (node 5), already more likely to fall into the high investment category, the probability is further boosted (in conditional sequence) by very small budget deficits (or surpluses), a good business environment (as captured by the BERI indices), low terms of trade volatility, and a low share of government consumption.

[9] Another way of addressing this problem is to exclude I/GDP from the potential explanatory variables in the growth tree. In that case, high population growth (with a threshold of 2 percent per year) and high inflation (above 9 percent per year) are the most important variables determining low output growth.

Figure 3: Determinants of Investment



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All decision criteria in percent, unless otherwise stated

Figures in italics are the probability of high growth, conditional on being at the current node

5 Conclusion

Following a productive decade of intensive research, empirical growth economics has identified a rich, and still expanding, set of factors found to be "significant" determinants of growth. Yet cross-country growth regressions appear to be fragile, with results depending upon the precise sample and estimation technique. Few determinants seem to be robustly related to growth. Both features are compatible with pervasive non-linearities: if the growth elasticities of factors vary with the magnitude of the factor, and depend on the size and presence of other factors, most of the growth determinants identified to date may indeed be significant for a sizable subset of observations, but at the same time, small changes in sample composition may change the significance and size of coefficients estimated in standard cross-section regressions.

In this paper, we used classification tree analysis to search for such non-linearities. The results indeed suggest that threshold effects and context-dependencies are part of the picture. In particular, the same factor may play very different roles in different subsamples, acting as a crucial discriminant between fast and slow growers in some circumstances, while being of little apparent importance in others. Taken at face value, they carry important implications. In particular, they caution against a piece-wise focus on individual growth determinants, suggesting instead a "holistic" approach that explicitly takes account of cross-dependencies between various growth determinants.

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