The quality of growth

Owen, Ann L. and Videras, Julio

Hamilton College

23 April 2012

The Quality of Growth

Ann L. Owen*
aowen@hamilton.edu

Julio Videras
jvideras@hamilton.edu

Hamilton College

April 2012

Abstract

We use latent class analysis to categorize development experiences. This technique allows us to consider a broad range of country characteristics including per capita income growth, health, inequality, environmental performance, and life satisfaction. We show that each of these indicators is important in explaining the classifications based on the quality of growth. We then predict membership in growth quality classes using many of the standard determinants of growth. We find that they are related to growth quality in a non-linear way and that population growth is more consistently related to our broader measure of growth quality than is typically found in standard growth regressions.

JEL Codes: O4, I3

Key words: long-run growth; standard of living; human development; finite mixture model

*Corresponding author: 198 College Hill Road, Clinton, NY 13323. 315-859-4419.

1 Introduction

Much of the recent growth literature focuses on explaining the determinants of the magnitude of the average annual growth rate over long periods of time because income per capita is often interpreted as a proxy for standard of living. In a traditional regression framework, the researcher must choose one dependent variable and growth of income per capita has been the most commonly used summary measure of economic development. In this paper, we propose an alternative method for characterizing development that takes into account multiple dimensions of the growth experience, including health, inequality, environmental performance, and life satisfaction. We find that groupings of countries based on the quality of growth can be explained by many of the traditional determinants of growth rates, however, many of these determinants affect the groupings in a nonlinear way. Furthermore, an important policy implication of our findings is that population growth plays a much more important role when the quality of growth is considered rather than just the magnitude of growth.

Thus, the main contributions of this paper are two-fold. The first contribution is methodological; we propose an alternative method, latent class analysis, for categorizing development experiences that allows us to consider a broad range of country characteristics. The second contribution is that we provide evidence about which country characteristics are 1) significant indicators of the quality of growth and 2) are predictors of the quality of the growth experience.

Our goal is related to the goal of those who develop indices that draw on several different indicators of development in order to capture a broader picture of the process of development. One of the most widely used indices is published by the United Nations Development Programme (UNDP), the Human Development Index (HDI).[1] The main HDI index draws on life expectancy, years of schooling, and income per capita. A value for each country is calculated and then countries are ranked by the index

[1] Although the HDI is widely used, other indices also attempt to rank countries based on a broader measures of economic performance. For example, the Happy Planet Index ranks countries based on ecological footprints, life satisfaction and life expectancy and the Prosperity Index ranks countries based on income per capita and life satisfaction. These indices use different methods of construction from the HDI, however, they are subject to similar criticisms.

and divided into four equally-sized groups: very high human development, high human development, medium human development, and low human development. The HDI index is widely used and publicized. Wolff, Chong, and Auffhammer (2011) discuss the many ways in which the HDI is influential: in determining prices of prescription drugs in developing countries, in the allocation of development aid, and in designing international agreements on environmental policy.

In spite of its importance, Wolff, Chong, and Auffhammer (2011) also highlight three critical sources of error in the calculation of the HDI: measurement error in the underlying data that is used to construct the index, changes in the HDI formula over time, and arbitrary cutoff values that are used to group the countries into the different classes.[2] We propose an alternative means of grouping countries based on latent class analysis that minimizes these errors. Importantly, latent class analysis is a model-based approach that allows us to view the underlying data such as life expectancy, schooling, or income, as indicators, with error, of the underlying latent variable, the quality of growth. We then use this latent variable to form groupings of countries, each with different quality of growth experiences.

Latent class methods are related to multivariate techniques such as cluster analysis, factor analysis, and principal components analysis that identify sub-groups in a population and generate common factors to summarize the variance in the data.[3] Latent class methods have several advantages over these techniques. First, latent class methods produce goodness-of-fit statistics that we use to identify the appropriate number of distinct classes (given the fit to the data and the number of parameters that we estimate); this makes the classification system less ad hoc than if we use cluster analysis requiring arbitrary cutoff values.[4] Second, in factor analysis the interpretation of the results depends on how the common factors are rotated; in latent class models, the interpretation of the classes is unique as it relies on the posterior probabilities of the indicators. Third, latent class models allow us to gauge the certainty

[2] Since the writing of Wolff et al. (2011), the HDI methodology was changed and a fourth grouping of countries was added in order to reduce the potential for misclassification of countries.
[3] See Hirschberg et al. (1991), Slottje (1991), McGillivray (2005), and Berenger and Verdier-Chouchane (2007) for examples of work that uses cluster analysis, factor analysis, or principal components analysis to consider multiple dimensions of development.
[4] Although researchers can use several rules to determine the number of clusters in cluster analysis, these rules do not depend on the models' log-likelihood as is the case in latent class models.

with which we classify individual countries into a specific group by estimating probabilities of group membership. Fourth, latent class methods allow expanding the model to include variables that help classify observations into classes; in our application, we use variables that are typically modeled as proximate determinants of growth rates (initial income, investment rates, secondary schooling, and population growth) to predict membership into classes. Finally, the latent class method assumes that the latent variable is discrete. This is a more desirable assumption if the final goal is to classify countries into discrete groupings. In contrast, if the classifications are based on a continuous variable such as that generated by factor analysis or principal components analysis, then ad hoc assumptions need to be made regarding the cutoff values for different groups.

More broadly, a latent class model can also be considered a finite mixture model. Some recent work in the growth literature has used finite mixture models to allow for classification of countries by the pattern of annual growth rates (Papp et al., 2005; Kerekes, 2012) or by the conditional distribution of growth rates in a traditional growth regression context (Bloom et al., 2003; Alfo et al., 2008; Owen et al., 2009). Our work is related to those results methodologically, however, the previous work studies the growth rate of per capita income as the main variable of interest. In contrast, we use latent class methods to define a multi-dimensional concept, the quality of growth, as the main variable of interest.

Although one aspect of the contribution of this paper is technical in nature, our work is related to a broad literature that attempts to capture complex dimensions of economic development. In seminal work, Sen (1985) focused poverty alleviation efforts on a capabilities approach that defined poverty with additional considerations beyond simply income levels and inspired the development of the HDI. Easterly (1999) considers 81 different indicators that describe governance, political instability, education, health, transport and communications, gender and class inequality, and what he calls "bads." He explores how these indicators change with the growth of per capita income, concluding that the quality of life does improve with growth, but that these changes are uneven and the strongest effects may be attributed to exogenous changes in global socioeconomic progress rather than home-country economic development.

While Easterly (1999) focuses on a broad range of indicators, others have focused on subjective well-being as a summary measure of the quality of life. Since Easterlin (1974) first pointed out that average levels of self-reported life satisfaction don't systematically increase with income per capita, many have explored the relationship between income growth and life satisfaction in order to explain this paradox. For example, Kahneman et al. (2006) attribute it to the "focusing illusion" which causes people to exaggerate the impact of additional income on happiness. Dynan and Ravina (2007) and Clark et al. (2008) suggest that life satisfaction depends on relative and not absolute incomes, while Stevenson and Wolfers (2008) and Sacks et al. (2010) use different methods and data to dispute the Easterlin paradox. Although Oswald (1997) also provides evidence that contradicts the existence of the paradox, he also downplays its importance, arguing that economic growth is only important to the extent that it makes people happier.

Others have focused on specific aspects of economic activity that might characterize different kinds of development. For example, Nordhaus (2000) argues that national income and product accounts are distorted because they do not include measures of non-market activity such as unpaid work, the value of leisure time, investment in human capital and changes in environmental quality and resources. An important implication of valuing a broader range of activities in national income accounting is that currently calculated growth rates of "income" per capita could be significantly different. Deaton (2008) focuses on a different aspect of welfare, relating health, income, and life satisfaction, arguing that that both health and income are linked in their relationship to higher levels of self-reported life satisfaction.

In selecting the indicators of quality of growth that we use in our study, we draw guidance from this previous work. As a result, we include per capita income growth in our analysis, but we also incorporate variables that measures inequality at the household level and also between men and women, environmental performance, health, and life satisfaction. Our work contributes to the existing literature by proposing an appropriate method to consider the multiple dimensions of the quality of growth. Furthermore, as we explain below, our results suggest that there is not one single indicator of growth quality that is sufficient by itself to describe the quality of growth in a large cross-section of countries, not even average values of self-reported life satisfaction. Of course, this finding could result from the fact that survey responses do not accurately measure true individual life satisfaction. A more interesting possibility, however, is that the average of individual life satisfaction measures does not capture all relevant aspects of welfare. Regardless of the reason, this finding emphasizes the importance of using a method that can incorporate multiple indicators of growth quality and test for their significance.

Of course, if countries with high income growth also have high quality and countries with low income growth have low quality, then the distinctions that we make are not important. However, as will be discussed more below, our findings suggest that the fastest growing group of countries do not have the highest quality and that not all low-growth countries have similar quality of growth. To the extent that different policies may be more effective in achieving better quality of growth than magnitude of growth, our results can have important policy implications.

Our results are developed in the next three sections. Section 2 describes our methods and data, Section 3 discusses the results, and Section 4 concludes.

2 Methods and Data

Latent Class Analysis

Intuitively, latent class analysis assumes that countries can be divided into a finite number of discrete classes. In our case, the latent variable that determines class membership is the quality of growth, with countries grouped in the same class having similar growth quality. We observe country characteristics such as growth rates of real income per capita, life expectancy, inequality, environmental performance, and life satisfaction and use those as indicators (with error) of the quality of growth which is not directly observed. Estimation is based on the idea that the probability of obtaining a specific pattern of characteristics is the average probability of the pattern given each class, weighted by the prior probability of class membership.[5] Specifically, let $i = 1,\ldots, I$, denote the countries. For each country we observe a set of six characteristics denoted $k = 1,\ldots,6$. Then, Y_{ik} is the value of characteristic k for country

[5] See Magidson and Vermunt (2005) for a more detailed discussion of latent class models and their estimation.

i and the pattern of characteristics for country *i* is represented by the vector, $\mathbf{Y}_i$. Under a generalized finite-mixture model, we assume a finite number of latent growth quality classes denoted *s* = 1,…, S. The discrete latent variable *X* represents the growth quality class. Then:

$$f(Y_i) = \sum_{s=1}^{S} P(X_i = s) \times \prod_{k=1}^{6} f(Y_{ik} \mid X_i = s) \qquad (1)$$

where

$f(Y_{ik} \mid X_i = s)$ is the density function for a multivariate normal distribution with a set of class-specific means, $\boldsymbol{\mu}_x$.

The class-specific mean for indicator *k* is modeled as a linear function:

$$\mu_x^k = \beta_0^k + \beta_{x0}^k \qquad (2)$$

where β_0^k is the intercept that is equal across all classes and β_{x0}^k is the effect on indicator *k* of being in class *x*.

Latent class analysis allows us to determine the smallest number of latent classes that account for the observed country characteristics. The equations above imply that the country characteristics are mutually independent of each other, given the class to which a country is assigned. Violation of this assumption causes a poor fit of the model. In order to estimate the model, we start by assuming only one class – mutual independence among country characteristics – and then increase the number of classes if the initial independence model does not fit the data adequately. However, in order to limit the number of classes estimated, we are able to model local dependencies of some country characteristics by creating a new joint dependent variable based on the interaction term using the two country characteristics that are not independent of each other. This procedure effectively adds another country characteristic to the estimation, but allows us to satisfy the independence assumption with fewer classes.[6]

[6] We identify these variables by examining bivariate residuals of the estimation. In our case, we model one local dependency between the gini coefficient and the ratio of female to male enrollment ratios.

To identify the model with the number of latent classes that best fit the data, we use the Bayesian information criterion (BIC) based on the model's log-likelihood. The models are fitted using Maximum Likelihood estimation and the results yield the conditional probabilities for membership in each class. These conditional probabilities are then used to define membership in each of the classes. Because the likelihood functions for these models can be complex, we examine 10,000 starting values in our estimation procedure in order to ensure that we achieve a global maximum.[7]

An interesting way that we can extend the basic model is that we can use additional country characteristics to help predict class membership. These additional predictor variables are not indicators of the latent variable growth quality as the other variables in $\mathbf{Y_i}$ are. However, they help to predict the class membership of the individual countries. Specifically, we modify the probability structure of the model to allow a vector of predictor variables, $\mathbf{Z_i}$ to influence the probability of class membership. Let $r = 1,\ldots, R$ denote the predictor variables. The model now becomes

$$f(Y_i) = \sum_{s=1}^{S} P(X_i = s \mid \mathbf{Z}_i) \times \prod_{k=1}^{6} f(Y_{ik} \mid X_i = s, \mathbf{Z}_i). \qquad (3)$$

And, the linear predictor for the class specific mean becomes:

$$\mu^k_{x,Z_i} = \beta^k_0 + \beta^k_{x0} + \sum_{r=1}^{R} \beta^k_r \cdot z_{ir} \qquad (4)$$

where β^k_r is the marginal effect of predictor r on indicator k.

This extension is intuitively appealing because we can simultaneously estimate class membership as well as determine what country characteristics influence class membership. In other words, we not only identify growth quality regimes but also are able to determine the influence that specific country characteristics have on the probability of membership in any given regime. We will take advantage of this extension in our work because it allows us to test if the standard determinants that are typically used in growth regressions also explain a broader definition of welfare improvement that incorporates not only

[7] We use Latent GOLD to perform the estimation.

the magnitude of the growth rate but also the quality of that growth. To the extent that our results highlight different determinants, different policy conclusions would result.

Furthermore, this method is distinct from the development of an index that attempts to capture multiple dimensions of development, such as the Human Development Index (HDI), for a number of reasons. Importantly, the number of groupings is determined by the data itself and is not imposed in an ad hoc fashion by the researcher. In addition, because it is a model-based, probabilistic assignment, we are able to develop test statistics based on statistical theory that allow us to confirm the importance of each country characteristic in determining growth quality. A final advantage of the model-based approach is that we are able to assume that the country characteristics are indicators with error of the latent quality of growth and we are able to compute the probability of class membership for each country, giving us some sense of the confidence with which we assign a country to a class.

Data

To implement the estimation, we need to assemble a data set that contains country characteristics that are indicators of the quality of growth and also additional country characteristics that may help to predict class membership that is defined by growth quality. In doing so, we need to keep in mind that this estimation technique is data-intensive. For each variable that we include, we increase the number of parameters we estimate by the number of classes. For example, in a four class model, adding one more indicator variable requires the estimation of five additional parameters. (The intercept in Equation 2 plus class-specific intercepts.) For typical cross-country data sets, that can be problematic so parsimony is a desirable characteristic of our model and we need to be cautious in selecting our indicators.

Motivated by the literature mentioned in the introduction, we choose six variables as indicators of growth quality: the average annual growth rate of real income per capita over the period 1990 to 2005, the ratio of female to male secondary school enrollment rates, the Gini coefficient, life expectancy, life satisfaction, and the 2010 Environmental Performance Index.[8] Enrollment rates, Gini coefficients and life expectancy are all as of 2005 and life satisfaction is based on surveys conducted during the time period 2000 to 2008.[9] We measure these variables near the end of the period over which we measure growth because they are indicators of the results of the growth that was recently experienced. Thus, our indicators of the quality of growth include measures of the magnitude of the growth rate as well as inequality (both at the household level and by gender), health, environmental sustainability, and overall life satisfaction. Admittedly, it is reasonable to choose a different combination of indicators to achieve the goals of this paper; however, what is important for our work is not that the specific variables precisely measure the quality of growth, only that they are indicators, with error, of growth quality.

We also extend our model to use variables that are typically used in growth regressions to determine if those variables can predict membership in a growth quality class. Specifically, we use the natural log of initial income, a measure of corruption control from the World Bank Governance Indicators, and the natural logs of investment, secondary school enrollment and population growth, averaged over the time period 1990 to 2005. Descriptive statistics and data sources can be found in the appendix.

3 Results

Initial Classification

The fit statistics for latent class models containing from one to five classes are in Table 1. As discussed above, the model that best fits the data is the one with the lowest BIC. In this case, it is the four class model. While the BIC imposes a penalty for including additional parameters, a stricter penalty is imposed by the Corrected Akaike Information Criterion (CAIC).[10] We use that as a secondary criterion, and the

---

[8] Although our work is somewhat critical of the use of indices, in this case, we use the Environmental Performance Index simply as an indicator, with error, of the underlying environmental performance of the country. Thus, we do not use this index to rank countries or use ad hoc cutoffs to group the countries.

[9] We obtained the life satisfaction data from supplementary tables released with the Happy Planet Index. The underlying source of the data is the Gallup World Poll and the World Values Survey.

[10] The BIC= -2LL + log(N)J and the CAIC=-2LL+log(N+1)J, where *LL* is the value of the log likelihood, N is the sample size, and *J* is the number of parameters estimated.

values for the CAIC reported in Table 1 also guide us to select the four-class model. We also report in Table 1 an estimation of the total classification error of the model. This is an estimate of the average probability of misclassification obtained by taking the estimated probability of belonging to the assigned class for each country, subtracting it from one, and then averaging this classification error across all the countries. The classification error cannot be used to choose between models because choosing the lowest classification error would always result in a one class model; however, after the model is selected, it can tell us the certainty with which we classify countries. In this case, the average misclassification error is only .046, indicating a fairly low rate of error.

In Table 2, we present the estimates of β_{x0}^{k} from Equation 2. These are the effects of class membership on each indicator. They are normalized to sum to zero so the signs and significance of these parameters indicate the manner in which they help to classify countries. For example, looking across the first row of Table 2, we see that higher values for life expectancy are associated with a greater likelihood of being in class 1 and class 4 and a lower probability of being in class 3. The fact that the estimated parameter for life expectancy is more than twice as big for class 4 as it is for class 1 suggests that having the highest values for life expectancy is associated with the highest probability for membership in class 4. Similarly, having a high value for the female to male enrollment ratio is associated with a higher probability of being in class 1 and 4, but a lower probability of being placed in class 3. Interestingly, it is not significantly associated with membership in class 2, indicating that this particular indicator is not associated with the latent variable, growth quality, in a linear way. This result is in contrast to the usual treatment of these types of indicators in an index such as the HDI in which a homogenous relationship between indicators and outcomes for all countries is typically assumed.

There are several interesting results in Table 2. The results for growth rates suggest that higher growth rates help to classify countries into Class 1 and out of Class 3 but that they do not significantly distinguish countries for membership in Class 2 or 4. In contrast, higher income inequality as measured by the Gini coefficient is associated with lower probabilities of being in Class 2 or 4 and a higher probability of being in Class 3. Better environmental performance is more likely in Class 1and Class 4, but less likely for countries in Class 3. Finally, higher values for life satisfaction are more likely in Class 1 and 4; they are less likely in Class 2 and 3. It is important to note that each indicator is statistically significant for at least two classes, suggesting that all these are meaningful indicators of the underlying latent variable. In other words, a variable such as average life satisfaction does not, by itself, capture all of the important dimensions of growth quality.

The parameters displayed in Table 2 help to sort countries into classes and define the characteristics of those classes. In Table 3, we provide a profile of the classes generated by this estimation. Class 1 is the largest class with 30 percent of the countries falling into this group. We can characterize this as a high growth, medium quality class. It has the highest average for the annual growth rate at 2.3 percent, but also has the highest level of average income inequality. All other indicators of the quality of growth indicate that this fast growing, high inequality group has the second highest level for life expectancy, environmental performance, and life satisfaction. Interestingly, the average ratio of female to male enrollment ratios indicates that there are actually more female students than male students in secondary schools, on average, in these countries. This and the high levels of inequality may be symptoms of the fast growth as the economies transition to becoming more fully developed.[11]

Class 2 is the second largest class, with 25 percent of the sample. This class might be characterized as a low growth, medium quality class. It has the lowest average growth rate of all four classes, yet it performs better than some of the other classes on the measures of growth quality. It has the second highest level of average income equality, but the third lowest values for other measures of growth quality such as life expectancy, female/male enrollment ratios, environmental performance and life satisfaction.

[11] It is possible to estimate a latent class model in which countries switch classes via a Markov process. (See, for example, Kerekes, 2012.) However, the data requirements of such a model are substantial, requiring us to observe all countries over a longer time period, and we are unable to estimate it given the available data. Given that we examine only a fifteen year period, the restriction that countries stay in one class for that time period is a reasonable assumption for most countries.

Class 2 is most interesting in comparison to Class 3, another low growth group of countries. However, Class 2 seems to be distinguished from Class 3 in that Class 3 has the worst performance of all the other indicators of quality, with an average life expectancy of only 53 years, a female/male enrollment ratio at 76 percent, a Gini coefficient of 45, by far the lowest level of environmental performance, and the lowest level of life satisfaction. The comparison between Class 2 and Class 3 reveals the importance of not only examining the magnitude of the growth rate but also the quality of that growth. Our methods allow us to simultaneously consider all of these indicators, rather than focus on just one of them or focus on them separately. Although the growth rates are similar for the typical country in Class 2 and Class 3, the quality of life in the typical Class 2 country is much higher.

Finally, Class 4 is the smallest group, with approximately 22 percent of the sample. This class might be characterized as medium growth, but high quality. The average growth rate for countries in this class is lower than that for Class 1 in a meaningful way. However, these countries have the highest average life expectancy, equality in schooling for females and males, the lowest level of income inequality, and the highest level of environmental performance and life satisfaction.

As a comparison to other means of classifying development experiences of countries, the bottom rows of Table 3 provide the average value for the 2010 HDI index as well as the range. The HDI index used here takes into account life expectancy, schooling, and income per capita. Because it uses a more limited number of characteristics to categorize countries, we would naturally expect that the groupings would not be the same. Furthermore, another difference would be generated simply because we are interested in understanding the quality of growth rate of income whereas the HDI uses the level of income. However, the fact that the results in Table 2 suggest that all six indicators that we use are significant in explaining class membership suggest that our methods capture a meaningful classification of countries based on a broader set of indicators. It is interesting to note that the World Bank also releases additional indices (such as an inequality adjusted HDI and a gender equality index) and analysis related to the main HDI index that considers some of the concepts that we are able to consider simultaneously in our methods.

The comparison to the HDI ratings show that, on average, our classifications correspond to those of the HDI, with Class 4 countries obtaining the highest average rating, followed by Classes 1, 2, and then 3. However, the range of the HDI index for the countries in the group suggest that there is substantial overlap in these ratings across the classes.

A more direct comparison to the HDI would apply latent class analysis to the same data that is used in the construction of the HDI (life expectancy, expected years of schooling, mean years of schooling and gross national income per capita). We perform this exercise and report the fit statistics for a number of models in Table 4. Note that because we use a different set of variables to perform the analysis, we are able to use all 187 countries ranked by the HDI, thus, the HDI sample is larger than the 110 country sample used above. The fit statistics in Table 4 tell us that if we use the BIC to select the model, we would select a 6-class model, however, the CAIC guides us towards a 5-class model. Recall, that the CAIC imposes a stronger penalty for additional parameters. The size of our data set (187 countries) combined with the fact that the improvement in the BIC from the 5 to 6 class model is very small, leads us to choose the more parsimonious 5-class model. In fact, when we examine the difference in the class profiles between the 5 and 6 class models, we see that the sixth class is created by splitting off a small portion of the countries that are in Class 5 (only 2 percent of the sample). The first four classes are similar in both models. Thus, the two models lead us to the same overall qualitative conclusions.

Descriptive statistics for the 5-class model are in Table 5. Although, on average, the classes we identify clearly correspond to the HDI rankings, these results suggest a different classification system for countries. First, rather than a four class model that is the *de facto* model choice for the HDI rankings, the data suggest additional classes.[12] Furthermore, the HDI procedure of imposing that the classes be of equal size is not supported by the data.[13] For example, the findings reported in Table 5 show that the

[12] The five class model is also supported by a likelihood ratio test comparing the four and five class models. The bootstrapped p-value for this test is .000. However, when we restrict the sample to only the 110 countries in our original sample, the model that best fits that data is a four class model.

[13] In fact, if we were to force the four class model in spite of the fit statistics reported in Table 4, we find that the four classes would not be of equal sizes even then, with the largest class being 45 percent of the sample and the smallest class being only 8 percent of the sample.

most developed countries (class 4) are a much smaller percentage of the sample at 14 percent. The least developed (class 1) are a slightly larger fraction of the sample at 28 percent, with the remaining countries being split among three other classes.[14] Thus, there are important differences in the two classification systems even when the same data is used in the analysis. In other words, while some of the differences in our conclusions are a result of consideration of additional dimensions of development, other differences are a result of differences in methods.

Turning back to our main results that take into account broader dimensions of development, we present the list of countries in each class and their associated probabilities of class membership in Table 6. Interestingly, while many countries are classified with near certainty, several countries are more difficult to group. For example, Zambia is located in the low growth, low quality class with a probability near one, however, some of the Eastern European countries such as Hungary, Romania, and Estonia show up in Class 1 with significantly lower probabilities. Being able to provide estimates of probabilities of classification is a result of our model-based methods and is a significant advantage over the classifications based on values of indices.

Determinants of Class Membership

Now that we have classified countries by quality of growth, we revisit traditional analyses of growth determinants to explore how the country characteristics that have been associated with higher magnitudes of growth rates are also associated with overall growth quality. To do this, we extend the initial model by adding the predictor variables, Z, to the estimation. As predictors, we use variables that are motived by the human-capital augmented Solow model estimated in Mankiw, Romer, and Weil (1992) and widely used in the growth literature: the log of initial income per capita, the log of the average investment rate, secondary schooling enrollment rate, and population growth over the period. Given the prominence of quality of institutions in the growth literature, we also include a measure of governance: corruption control.

[14] Note that some high-income oil-producing countries are in Class 5, producing a high average income level for that class, even though other human development indicators are at more moderate levels.

We simultaneously estimate the coefficients on the predictor variables and the parameters on the six cluster variables and obtain a model with four classes. Although we do not report the detailed fit statistics for this model here, we do confirm that the BIC and the CAIC both indicate that a four class model fits the data best in spite of the increased number of parameters that we estimate and the loss in sample size due to the additional data that we use. (We only have data available for all variables for 85 countries, compared to 110 countries for the model without predictor variables.) Furthermore, the qualitative nature of the four classes is the same in both models.[15]

The results for the coefficients on the predictor variables appear in Table 7. These coefficients have also been normalized so that across each row, the coefficients add up to zero. Therefore, as before, positive and statistically significant values indicate that this country characteristic is associated with a higher likelihood of belonging to a specific class while negative and significant values are associated with a lower likelihood. Of course, investment, education, corruption, and population growth may not be exogenous to the quality of growth and we are cautious about making claims about causality. Instead, we present these results as a comparison to typical growth regressions.

Several interesting results emerge from Table 7. First, initial income is only a significant predictor of class membership for Class 2, the low growth, medium quality group, and Class 4, the medium growth, high quality group. Higher income is associated with a lower probability of membership in Class 2 and a higher probability of membership in Class 4. It is not a significant predictor sorting countries into Class 1. The negative coefficient on initial income for Class 3, does not quite achieve statistical significance at the 10 percent level. It is interesting to interpret this result in conjunction with the result for investment in which higher values of investment is associated with a higher likelihood of being in both Class 2 and Class 4. Recall that both Class 2 and Class 3 have low growth rates, but that Class 2 has higher values for variables that indicate the quality of that growth. Thus, while both groups of

[15] We also confirmed that when we estimate the initial model with only these 85 countries that the parameters we obtain have similar signs, significance and magnitude to those reported in Table 2.

countries have low income and low growth rates, higher investment rates increase the probability of belonging to the better growth quality class.

It is notable that population growth is the only variable that is significant in explaining membership in all four classes. Typically, this variable enters growth regressions somewhat inconsistently and is not found to be one of the robust determinants of growth by Levine and Renault (1992). However, our estimation finds that population growth is important when we not only consider the magnitude of growth rates but the quality of the growth experience. Given that several of our indicators of growth quality might reasonably decrease as larger populations drain resources from the economy, this result seems reasonable. Higher population growth sorts countries out of Classes 1, 2, and 4 and into Class 3. This is an important finding because Class 3 is the grouping that has both low growth and low quality of life measures. One interpretation for this strong finding of the importance of population growth is that while it may exercise a small or inconsistent role in determining growth rates, it plays a much more important role in determining the quality of that growth experience.

In contrast, we find that higher levels of schooling are a significant predictor of the quality of growth by affecting the probability of membership for only two classes, Class 2 and Class 4. We see that higher schooling sorts countries into Class 2. The comparison between Class 2 and Class 3 is important here as well and this result indicates that schooling may also be a characteristic that allows low income and low growth countries to have higher quality of life. The coefficient on schooling in Class 4 is negative, however, it is important to realize that this is after controlling for all other variables, including initial income.

Finally, our results support a non-linear effect for corruption control as well. It is significant in explaining membership in only one class, with higher levels of corruption control reducing the probability that a country is in Class 2. In comparing the two low-growth groups, Class 2 is the one that has higher investment, higher enrollment rates and lower population growth. Thus, one interpretation of this result is that a reason why this group has poor growth performance is primarily due to higher levels of corruption. Interestingly, our results do not support an important role for corruption control in all classes. Perhaps it is the vulnerability caused by low income that makes corruption control more important in this group of countries.

4 Conclusion

Our results demonstrate that examining only the magnitude of growth rates is insufficient to characterize the process of development. Countries with similar growth rates can have very different growth quality experiences. While some have attempted to capture the multiple dimensions of development using indices such as the HDI, our approach avoids the ad hoc nature of the construction of these indices by employing a model-based strategy, latent class analysis. There are multiple advantages to this approach. One of them is that we are able to directly test whether the variables that we use are indicators of the multi-dimensional latent country characteristic that we are attempting to measure. In addition, we do not have to impose arbitrary cutoffs for membership in different classes and are able to statistically test which model fits the data best. For this reason, the method we employ has practical advantages for policy making: it assumes that the quality of growth is a discrete variable that allows for the determination of groupings of countries as opposed to developing a continuous index and then relying on ad hoc cutoff points to determine groupings. Finally, we can quantify the certainty with which we classify individual countries.

Our results highlight a strong relationship between low population growth and high quality growth experiences. Furthermore, we show that corruption control has the most significant marginal effect in low income countries that might otherwise have some promise in higher investment rates, enrollment rates, and low population growth.

There is more work to be done in understanding the determinants of a high quality growth experience. In particular, our work has examined a point in time characterization of the quality of growth in a cross-section of countries. Because of this, we are unable to distinguish between countries that may be in a particular phase of development that is part of the process of transitioning to a more developed state vs. countries that may be stalled in a low-growth-quality steady state. Furthermore, the method lends itself to testing key hypotheses about the deeper determinants of growth quality classes that are motivated by the current growth literature such as the importance of institutions, openness, or natural resource endowments.

Over time, progress on this question will be facilitated by the availability of additional data on the long-term experience of countries. Nonetheless, the latent class analysis technique shows promise in allowing us to understand these complex relationships and the results we present in this paper serve to illustrate the importance of considering multiple dimensions of the development experience.

Acknowledgements: We are grateful for helpful comments from Lewis Davis.

References

Alfo, M., Giovanni, T., & Robert, J. W. 2008. "Testing for Country Heterogeneity in Growth Models using a Finite Mixture Aproach." *Journal of Applied Econometrics, 23*: 487–514.

Berenger, Valierie and Audrey Verdier-Chouchane. 2007. "Multidimensional Measures of Well-Being: Standard of Living and Quality of Life Across Countries" *World Development* 35(7): 1259-1276.

Bloom, D. E., David, C., & Jaypee, S. 2003. "Geography and Poverty Traps." *Journal of Economic Growth, 8*: 355–378.

Clark, Andrew E., Paul Frijters, and Michael A. Shields. 2008. "Relative Income, Happiness, and Utility: An Explanation for the Easterlin Paradox and Other Puzzles." *Journal of Economic Literature*, 46(1): 95-144.

Deaton, Angus, 2008. "Income, Health and Well-Being around the World: Evidence from the Gallup World Poll." *Journal of Economic Perspectives* 22(2): 53-72.

Dynan, Karen E. and Enrichetta Ravina, 2007. "Increasing Income Inequality, External Habits, and Self-Reported Happiness." *American Economic Review* 97(2): 226-31.

Easterlin, Richard A. 1974. "Does Economic Growth Improve the Human Lot? Some Empirical Evidence." In Paul A. David and Melvin W. Reder, eds., *National and Households in Economic Growth: Essays in Honor of Moses Abramowitz.* Academic Press.

Easterly, William, 1999. "Life During Growth." *Journal of Economic Growth* 4(3): 239-76.

Hirschberg, Joseph G., Esfandiar Moussoumi, and Daniel J. Slottje. 1991. "Cluster Analysis for Measuring Welfare and Quality of Life Across Countries." *Journal of Econometrics* 50(1-2): 131-150.

Kerekes, Monika, 2012. "Growth Miracles and Failures in a Markov Switching Classificaiton Model of Growth." *Journal of Development Economics* 98: 167-177.

Levine, Ross and David Renelt, 1992. "A Sensitivity Analysis of Cross-Country Growth Regressions." *American Economic Review* 82(4): 942-963.

Mankiw, N. Gregory, David Romer and David N. Weil, 1992. "A Contribution to the Empirics of Economic Growth." *Quarterly Journal of Economics* 107(2): 407-437.

McGillivray, Mark. 2005. "Measuring Non-economic Well-Being Achievement." *Review of Income and Wealth*. 51(2): 337-364.

Nordhaus, William D., 2000. "New Directions in National Economic Accounting," *American Economic Review* 90(2): 259-263.

Oswald, Andrew J. 1997. "Happiness and Economic Performance." *Economic Journal* 107(445): 1815-1831.

Owen, Ann L., Julio Videras and Lewis Davis. 2009. "Do All Countries Follow the Same Growth Process?" *Journal of Economic Growth* 14(4): 265-286

Paap, R., Franses, P. H., & Dijk, D. 2005. "Does Africa grow slower than Asia, Latin America and the Middle East? Evidence from a new data-based classification method." *Journal of Development Economics, 77*, 553–570.

Sacks, Daniel W., Betsey Stevenson, and Justin Wolfers, 2010. "Subjective Well-Being, Income, Economic Development and Growth." NBER Working Paper #16441.

Sen, Amartya. 1985. *Commodities and Capabilities* (Amsterdam: North Holland).

Slottje, Daniel J. 1991. "Measuring the Quality of Life Across Countries." *Review of Economics and Statistics* 73(4): 684-693.

Stevenson, Betsy and Justin Wolfers, 2008. "Economic Growth and Subjective Well-Being: Reassessing the Easterlin Paradox." *Brookings Papers on Economic Activity* (Spring): 1-87.

Wolff, Hendrik, Howard Chong and Maximilian Auffhammer, 2011. "Classification, Detection and Consequences of Data Error: Evidence from the Human Development Index," *The Economic Journal* 121: 843-870.

Table 1: Fit Statistics for Initial Classification

	Log Likelihood	BIC	CAIC	Classification Error
1-Class	-1602.8353	3266.777	3279.7768	0
2-Class	-1428.7975	2984.508	3011.508	0.0037
3-Class	-1357.0724	2906.865	2947.8645	0.0269
4-Class	**-1309.4177**	**2877.362**	**2932.3617**	**0.0463**
5-Class	-1287.917	2900.167	2969.1671	0.031

Table 2: Parameters for Initial Classification

	Class 1	Class 2	Class 3	Class 4
Life Expectancy	4.659***	0.072	-15.645***	10.914***
	(0.547)	(1.279)	(0.860)	(0.688)
Female/Male Enrollment	10.906***	1.087	-18.330***	6.337***
	(1.412)	(2.336)	(3.042)	(1.567)
Income Growth	0.0091***	-0.007	-0.0056*	0.003
	(0.002)	(0.005)	(0.003)	(0.002)
Gini	5.477	-3.918*	5.489***	-7.048***
	(4.244)	(2.230)	(1.675)	(1.554)
Environmental Performance	4.136***	-2.020	-14.885***	12.769***
	(1.531)	(2.762)	(1.345)	(1.755)
Life Satisfaction	0.626**	-0.400***	-1.756***	1.529***
	(0.296)	(0.102)	(0.150)	(0.164)

Table 3: Class Profiles (Mean Values)

	Class 1	Class 2	Class 3	Class 4
Class Size	0.2995	0.248	0.2366	0.2159
Life Expectancy	73.0708	68.4838	52.7666	79.3261
Female/Male Enrollment	104.9019	95.0826	75.6661	100.3327
Income Growth	0.0232	0.0072	0.0085	0.0175
Gini	44.7362	35.3409	44.7482	32.2114
Environmental Performance	64.7723	58.6162	45.7512	73.4046
Life Satisfaction	6.6023	5.5761	4.2201	7.5053
Mean HDI	0.734	0.597	0.449	0.888
HDI Range	.574 to .908	.458 to .707	.295 to .632	.744 to .943
Class Description	High growth, Medium quality	Low growth, Medium quality	Low growth, Low quality	Medium growth, High quality

Table 4: Fit Statistics for HDI Model

	Log Likelihood	BIC	CAIC	Classification Error
1-Class	-3692.0252	7425.899	7433.899	0
2-Class	-3403.6693	6896.267	6913.267	0.0293
3-Class	-3269.8345	6675.678	6701.678	0.028
4-Class	-3225.0329	6633.155	6668.155	0.0315
5-Class	**-3186.6616**	**6603.49**	**6647.49**	**0.0622**
6-Class	-3159.9817	6597.212	6650.212	0.058
7-Class	-3138.094	6600.517	6662.517	0.0663

Table 5: Class Profiles for HDI Model (Mean Values)

	Class 1	Class 2	Class 3	Class 4	Class 5
Class size	0.28	0.28	0.22	0.14	0.08
Life Expectancy	57.57	74.39	71.35	80.75	71.06
Mean Years of Education	4.00	9.11	7.73	11.19	8.40
Expected Years of Education	8.75	14.04	12.06	16.37	12.67
GNI per capita	$1,594	$12,758	$4,829	$32,148	$40,231
Mean HDI	0.433	0.760	0.651	0.893	0.768
HDI Range	.286 to .573	.698 to .835	.522 to .739	.840 to .943	.537 to .905
Class Description	Least Developed	Medium High Development	Medium Development, less education and income	Most Developed	Medium Development, more education and income

Table 6: Class Membership

Class 1		Class 2		Class 3		Class 4	
P(1)	Country	P(2)	Country	P(3)	Country	P(4)	Country
0.507	Algeria	0.566	Armenia	1.000	Benin	0.997	Australia
1.000	Argentina	0.996	Azerbaijan	1.000	Botswana	1.000	Austria
1.000	Belize	0.808	Bahrain	1.000	Burkina Faso	0.993	Belgium
1.000	Brazil	1.000	Bangladesh	1.000	Burundi	0.999	Canada
1.000	Chile	0.725	Belarus	1.000	Cameroon	0.997	Costa Rica
1.000	Dominican Rep	0.952	Bhutan	1.000	Chad	1.000	Croatia
1.000	Ecuador	0.808	Bulgaria	0.999	Djibouti	0.895	Czech Republic
1.000	El Salvador	1.000	Georgia	1.000	Ethiopia	0.997	Denmark
0.633	Estonia	0.985	India	0.999	Ghana	0.999	Finland
1.000	Guatemala	0.994	Indonesia	1.000	Guinea	1.000	France
0.928	Guyana	0.574	Iran	1.000	Kenya	0.999	Germany
0.656	Hungary	0.965	Kazakhstan	1.000	Madagascar	0.927	Greece
1.000	Ireland	1.000	Kyrgyz Rep.	1.000	Malawi	0.967	Israel
0.991	Jamaica	0.999	Lao PDR	1.000	Mali	0.995	Italy
0.668	Jordan	0.743	Latvia	1.000	Mauritania	0.998	Japan
0.926	Korea, Rep.	0.695	Lithuania	1.000	Mozambique	0.998	Netherlands
1.000	Malaysia	0.943	Macedonia	1.000	Namibia	0.996	New Zealand
0.996	Mexico	1.000	Moldova	1.000	Niger	1.000	Norway
1.000	Nicaragua	1.000	Mongolia	1.000	Nigeria	0.894	Slovenia
1.000	Panama	0.991	Morocco	1.000	Rwanda	0.993	Spain
1.000	Paraguay	0.998	Nepal	1.000	Senegal	1.000	Sweden
0.993	Peru	0.997	Pakistan	1.000	South Africa	1.000	Switzerland
0.955	Philippines	0.986	Russian Fed.	1.000	Togo	0.996	United Kingdom
0.981	Poland	0.982	Serbia	1.000	Uganda	0.927	United States
0.912	Portugal	1.000	Tajikistan	1.000	Yemen, Rep.		
0.569	Romania	0.991	Tanzania	1.000	Zambia		
1.000	San Marino	0.991	Turkey				
0.895	Slovak Republic	1.000	Ukraine				
0.964	Thailand	1.000	Uzbekistan				
0.925	Trinidad & Tobago						
0.966	Tunisia						
1.000	Uruguay						
1.000	Venezuela, RB						

Table 7:

	Class 1 High Growth, Medium Quality	Class 2 Low Growth, Medium Quality	Class 3 Low growth, Low quality	Class 4 Medium Growth, High Quality
$\ln(GDP_0)$	0.027	-4.607***	-1.812	6.392***
	(0.621)	(1.217)	(1.139)	(1.092)
ln(investment)	1.995	5.489**	-4.123	-3.361
	(1.926)	(2.339)	(4.003)	(3.455)
ln(pop growth)	-0.909**	-2.0454***	3.981***	-1.027**
	(0.373)	(0.505)	(0.866)	(0.403)
ln(sec enrollment)	1.425	4.654**	0.699	-6.778**
	(1.238)	(2.041)	(1.403)	(2.869)
Corruption Control	-0.354	-2.072*	1.346	1.08
	(0.570)	(1.152)	(0.856)	(1.414)

Appendix: Descriptive Statistics

Variable	Mean	Std. Dev.	Definition	Source
Cluster Variables				
Income Growth	0.02	0.02	Average annual growth rate of real per capita income 1990-2005	World Development Indicators
Life Expectancy	69.32	10.19	Life expectancy in 2005	World Development Indicators
Female/Male Enrollment Rate	95.55	15.24	Female to Male Secondary School Enrollment	World Development Indicators
Gini	40.70	9.65	Gini Coefficient 2005	World Development Indicators
Environmental Performance	60.68	11.93	Environmental Performance Index in 2010	Yale Environmental Performance Index
Life Satisfaction	6.15	1.39	Average levels of life satisfaction	Gallup World Poll and World Values Survey, 200-2008
Predictors				
$\ln(GDP_0)$	8.50	1.25	ln(gdp per capita in 1990)	World Development Indicators
Corruption Control	0.24	1.08	Corruption Control in 1996	World Bank Governance Indicators
ln(sec enrollment)	4.09	0.68	ln(secondary school enrollment averaged 1990-2005)	World Development Indicators
ln(investment)	3.07	0.20	ln(investment/GDP averaged 1990-2005)	World Development Indicators
ln(population growth)	0.09	1.11	ln(average annual population growth rate 1990-2005)	World Development Indicators