

Robustness Procedures in Economic Growth Regression Models

Dennis S. Mapa

ABSTRACT

A central question for empirical economics, particularly economic growth, is which explanatory variables to include and exclude in the regressions. This paper aims to identify variables strongly correlated with provincial income growth in the Philippines by applying robustness procedures in determining which variables are strongly correlated with income growth. The extreme bound analysis (EBA) and Bayesian Averaging of Classical Estimates (BACE) were applied to fifteen determinants of income growth from a data set consisting of 74 Philippine provinces for the period 1985 to 2003 to test which among the explanatory variables are strongly correlated to growth. The tests show that among the fifteen variables, five variables stand out as being robust. The log of initial income, the ARMM indicator, the expenditure GINI and its square and the proportion of young dependents are all considered as strongly correlated to growth.

Key Words/Phrases: Robust, Extreme Bound Analysis (EBA), Bayesian Averaging of Classical Estimates (BACE)

I. INTRODUCTION

Recent empirical studies on economic growth attempt to identify the factors explaining the differences in growth rates by regressing observed growth rate of a country or province on a number of variables that could possibly affect growth. The basic methodology consists of running regressions of the form, $y_i = \beta_0 + \beta_1 x_{1i} + \dots + \beta_k x_{ki} + \varepsilon$, using cross-country or intra-country data. In this model, y_i is usually defined as the economic growth rate of country (or province) i and x_1, x_2, \dots, x_k are explanatory variables which vary across researchers, while ε is the error term.

A central question for empirical economics, particularly economic growth, is which explanatory variables to include and exclude in the regressions. Sala-i-Martin (1997) indicates that this problem arises due to the fact that economic growth theory is not explicit on what variables matter for growth. With this problem, the strategy being used by empirical researchers consists of trying variables that are thought to be potentially important determinants of growth. But when one starts running regressions combining different variables, one finds that variable x_1 is significant when the regression includes x_2 but becomes insignificant when x_3 is included. Variables are significantly correlated with growth depending on which other variables are held constant. The question now is,

“Which variables should be included in the growth regression?” (Barro and Sala-i-Martin: 2004).

To answer this question raised by Barro and Sala-i-Martin, numerous robustness procedures were suggested. The very first of the robustness procedures was the extreme bound analysis (EBA) suggested by Leamer (1983) and used by Levine and Renelt (1992) to test the robustness of the variables in the growth regression using cross country data. And more recently, the Bayesian averaging of classical estimates (BACE) used by Doppelhofer, Miller, and Sala-i-Martin (2000) in examining the robustness of 67 explanatory variables in cross-country economic growth regressions. These three procedures are discussed in the following subsections.

A. Extreme Bound Analysis (EBA)

To identify whether variable z is robust, Levine and Renelt initially proposed using the extreme bound test which was first used by Leamer. The first step in this procedure is to estimate regressions of the form:

$$\gamma = \alpha_j + \beta_{yj}y + \beta_{zj}z + \beta_{xj}x_j + \varepsilon \quad , \quad (i)$$

where y is a vector of fixed variables that appear in all the regressions (in income growth regressions, these are usually the log of initial income and education), z is the variable of interest, and $x_j \in X$ is a vector of variables taken from the pool X of N variables available. One needs to estimate this regression or model for the M possible combinations of $x_j \in X$. For each model j , one finds and estimate, β_{zj} , and the corresponding standard deviation, σ_{zj} .

The next step is to compute for the lower and upper extreme bounds. The lower extreme bound for variable z is defined to be the lowest value of $\beta_{zj} - 2\sigma_{zj}$ and the upper extreme bound for z is defined to be the largest value of $\beta_{zj} + 2\sigma_{zj}$.

The extreme bound test for variable z states that if the lower extreme bound is negative and the upper extreme bound is positive, then variable z is not robust. This means that the variable is considered not robust if one finds at least one regression for which the sign of the coefficient, β_z , changes or becomes insignificant.

From their test, Levine and Renelt (1992) concluded that very few variables are robust. This means that the test is too strong for any variable to pass it. Also, under the EBA, all regressions are treated equally, no matter how poorly the regression fits. The statement of any one of the regressions carries a veto.

B. Bayesian Averaging of Classical Estimates (BACE)

Since Levine and Renelt's test is considered too strong by some researchers for any variable to really pass it, Sala-i-Martin (1997) suggests moving away from the extreme bound test and instead assign some level of confidence to each of the variables. One way to do this is to look at the whole distribution of the estimators of β_z .

To identify which variables are robust, Doppelhofer, Miller, and Sala-i-Martin (2000) represented a model, M_j , as a length K binary vector in which a one indicates that a variable is included in the model and a zero indicates that it is not. Then the prior probability of model j , as specified by the researcher, is given as:

$$P(M_j) = \left[\prod_{i=1}^K M_{ji} \frac{\bar{k}}{K} \right] \left[\prod_{i=1}^K (1 - M_{ji}) \left(1 - \frac{\bar{k}}{K} \right) \right] \quad (\text{v})$$

where k_j is the number of included variables in model j , \bar{k} is the prior mean model size, and M_{ji} is the i th element of the vector.

In the case of equal prior inclusion probabilities for each variable, the prior probability of model j given above is simplified to:

$$P(M_j) = \left(\frac{\bar{k}}{K} \right)^{k_j} \left(1 - \frac{\bar{k}}{K} \right)^{1-k_j}, \quad \forall j = 1, \dots, J \quad (\text{vi})$$

The weights can then be computed using the prior probabilities. The weight of a given model is normalized by the sum of the weights of all possible models with K possible regressors:

$$P(M_j | y) = \frac{P(M_j) T^{-k_j/2} SSE_j^{-T/2}}{\sum_{i=1}^{2^K} P(M_i) T^{-k_i/2} SSE_i^{-T/2}}, \quad \forall j = 1, \dots, J \quad (\text{vii})$$

where T is the sample size and SSE_i is the OLS sum of squared errors under model i . From equation (3), equation (4) becomes:

$$P(M_j | y) = \frac{SSE_j^{-T/2}}{\sum_{i=1}^{792} SSE_i^{-T/2}}, \quad \forall j = 1, \dots, 792. \quad (\text{viii})$$

The normalized weights for models where the number of included variables in every model fixed are just a function of the OLS sum of squared errors of the models.

Therefore, the posterior mean of β ,

$$E(\beta | y) = \sum_{j=1}^{2^k} P(M_j | y) \hat{\beta}_j \quad (\text{ix})$$

where $\hat{\beta}_j = E(\beta | y, M_j)$ is the OLS estimate for β with the regressor set that defines model j , is computed as the weighted average of the OLS estimates using the OLS sum of squared errors:

$$E(\beta | y) = \sum_{j=1}^{792} \left(\frac{SSE_j^{-T/2}}{\sum_{i=1}^{792} SSE_i^{-T/2}} \right) \hat{\beta}_j \quad (\text{x})$$

Moreover, the posterior variance of β given by:

$$Var(\beta | y) = \sum_{j=1}^{2^k} P(M_j | y) Var(\beta | y, M_j) + \sum_{j=1}^{2^k} P(M_j | y) [\hat{\beta}_j - E(\beta | y)]^2 \quad (\text{xi})$$

is also a function of the OLS sum of squared errors:

$$Var(\beta | y) = \sum_{j=1}^{792} \left(\frac{SSE_j^{-T/2}}{\sum_{i=1}^{792} SSE_i^{-T/2}} \right) Var(\beta | y, M_j) + \sum_{j=1}^{792} \left(\frac{SSE_j^{-T/2}}{\sum_{i=1}^{792} SSE_i^{-T/2}} \right) [\hat{\beta}_j - E(\beta | y)]^2 \quad (\text{xii})$$

II. DETERMINANTS OF PROVINCIAL PER CAPITA INCOME GROWTH RATE (1985 TO 2003)

An econometric model is built to study the determinants of economic growth, using provincial data from 1985 to 2003. In doing this study, the authors hope to make empirical contributions to the study of economic growth, specifically in the Philippines. First, the data set of provinces covering a period of 18 years is quite a rich country level data sufficient to study the determinants of income growth. Second, the Philippine data is collected using uniform definitions of the variables. Third, there is no exchange rate variation between the provinces and price variation across provincial domains is smaller than across countries.

A. Theoretical Framework of the Model

This paper uses an intra-country income growth equation derived from the neoclassical Ramsey-Cass-Koopmans model similar to the approaches used by Bloom and Williamson (1997), Bloom, Canning and Malaney (1999) and Radelet, Sachs and Lee (1997).

The econometric model estimates the direct effect of the population dynamics, particularly the impact of the young population (0 to 14 years), on economic growth. At the same time, the model also estimates the effects of other determinants of economic growth. This reverse causality creates a problem in the estimation of the regression model, resulting to biased and inconsistent estimates. This problem is remedied through the introduction of instrumental variables into the regression equation.

B. Data and Variable Specification

The data set consists of 74 provinces with variables recorded for the period 1985 to 2003, covering 18 years¹. The dependent variable of the econometric model is the average growth rate of provincial per capita income, as estimated from the FIES, from 1985 to 2003, measured in 1997 pesos and adjusted for price differences in the provinces. The explanatory variables are defined as follows:

- (a) *Initial economic conditions*: (i) initial mean per capita income, (ii) initial human capital stock as measured by average years of schooling of the household head, (iii) mortality rate per 1,000 of 0 to 5 year-old children, (iv) infrastructure index measured as the average of binary variables indicating presence of street pattern, highway, telegraph, postal service, community waterworks and electricity, and (v) expenditure GINI ratio and its square, as a measure of inequality;
- (b) *Initial geographical conditions*: (i) an indicator variable, landlock, with value 1 if the province is landlocked and 0 otherwise, (ii) an indicator variable for the provinces of ARMM, namely, Basilan, Lanao del Sur, Maguindanao, Sulu and Tawi-Tawi, and (iii) the average annual number of typhoons;
- (c) *Initial demographic conditions*: (i) proportion of young dependents in 1985 defined as the ratio of the population aged 0 to 14 to the total population and (ii) net migration defined as the number of within country net migrants that is, the in-migrants less the out-migrants relative to the province during the period 1985 to 1990;
- (d) *Time-varying policy variables* (variables that measure the difference of specific policy variables from 1988 to 2003): (i) electricity access defined as the change in the proportion of households with access to electricity, (ii) change in road density defined as the proportion of roads (adjusted for quality differences), and (iii) the Comprehensive Agrarian Reform Program implementation defined as the cumulative CARP accomplishment to 1990 potential land reform area; and,

¹ Note that the data set includes only 74 provinces, instead of the current 79 provinces. The geographical boundaries of the provinces were kept constant throughout the period 1985 to 2003.

(e) *Neighborhood effects*: a variable measuring the average growth rate of per capita income of the neighboring provinces (1985 to 2003) using a contiguity measure.

C. Results of the Econometric Models

The results of the intra-country regression models are given in table 1. The regression models are representative specifications from the growth literature that includes initial income, human capital variable (education), measure of inequality, geographical factor, institutional conditions and demographic variables.

The magnitude of the coefficient of the natural logarithm of initial income (at -3.0720 for model 1) implies that (conditional) convergence of provincial income occurs at the rate of about 3% per year. Note, however, that this convergence is conditional in that it predicts a higher growth in response to a lower starting provincial income per person if the other explanatory variables are held constant. At a conditional convergence rate of 3%, it would take about 23 years before half the initial gap, between the average income per person (in 1985) and the steady state income per person, will be eliminated (half life of convergence).

For all models, the population variable, proportion of young dependents, has a negative and significant effect on income growth. The estimated coefficient of -0.09 (for model 1) implies that a one-percentage point reduction in the percentage of young dependents in 1985 results in an estimated 9 basis points increase on the average growth rate of income per person from 1985 to 2003, all things being the same. The absolute figure of 9 basis points might be small at first glance but it should be considered that the estimated increase in income growth, as provided by the model, is cumulated over 18 years which can result in a significant increase in the 2003 per capita income.

Table 1. Determinants of Provincial per Capita Income Growth Rate

Dependent variable is average provincial per capita income growth rate from 1985 to 2003.

Variable	MODEL 1 ^a	MODEL 2 ^a	MODEL 3 ^b	MODEL 4 ^y
Log of initial income	-3.0720*** (0.429)	-2.4620*** (0.493)	-3.1957*** (0.4839)	-3.4786*** (0.419215)
Education	0.1483 (0.164)	- -	0.136 (0.1869)	0.2715* (0.150888)
Proportion of young dependents	-0.0912*** (0.031)	-0.0752* (0.04)	-0.1306** (0.0534)	-0.1011** (0.040808)
Expenditure GINI	43.0895** (19.018)	46.9507** (20.72)	49.1290** (21.9622)	68.4040*** (13.90763)
Square of expenditure GINI	-64.1636** (26.271)	-69.3848** (28.292)	-73.1441** (29.619)	-99.7146*** (19.75772)
ARMM dummy	-2.2910*** (0.668)	-2.1451*** (0.671)	-2.2077*** (0.6602)	-1.1409*** (0.340229)
Net migration	-0.0080* (0.004)	- -	-0.0051 (0.0069)	-0.0060* (0.003346)

Neighborhood effect	-0.3257*	-0.4381**	-0.3640*	-0.3852**
	(0.176)	(0.211)	(0.2139)	(0.175629)
Infrastructure index	-	1.6724**	-	-
	-	(0.793)	-	-
Change in electricity	-	0.0091	-	-
	-	(0.008)	-	-
Constant	28.2902***	21.2817***	30.2969***	27.4932***
	(5.365)	(7.049)	(7.131)	(5.435676)
N	74	74	74	74
R-squared	0.5599	0.5657	0.5944	0.564

*** significant at 1%; ** significant at 5%; * significant at 10%;

α : Estimation is by least squares.

β : Estimation is by two-staged least squares.

γ : Estimation is by generalized method of moments.

Note: Standard errors are reported in parentheses and are White's heteroscedasticity consistent standard errors.

The measures of initial inequality (expenditure Gini and its square were used instead of income or land (asset) Gini) are both significant but with opposite signs. The coefficient of inequality has a positive sign, while its square has a negative sign, all things being the same. The opposite signs of the coefficients imply that the relationship between inequality and income growth follows that of an inverted U shape. In particular, low levels of inequality do not create hindrance for growth, but high levels of inequality are associated with lower income growth. In fact, there is a “turning point” where below this value, inequality has a positive effect on income growth but above this value it has a negative effect on income growth. This “turning point” is estimated to be 0.34, which is about the same as the average GINI for the 74 provinces. It means that GINI values below 0.34 (GINI coefficient is between 0 and 1) have positive effects on the average income growth while GINI values higher than 0.34 have constricting effects on income growth.

The location variable ARMM has a negative and significant impact on the average provincial income growth suggesting that these provinces have been experiencing “growth discount” over the years, relative to the other provinces. Provinces in the ARMM region have lower average per capita income growth of about 2.29 percentage points compared to that of the average of the other provinces, all things being equal.

Net migration has a negative and significant effect on average provincial growth rate. The estimated coefficient implies that for every 10,000 net migrants entering the province during the period 1985 to 1990, the estimated average growth rate per person decreases by 0.08 percentage point (or 8 basis points) all things being the same.

To capture potential spillover effects which indicates how the average growth rate of per capita income in the province is affected by its neighboring provinces, after conditioning for the initial level of income per person, a “neighborhood effect” is introduced in the regression model. This variable is computed as the average growth rate of the

neighboring provinces (from 1985 to 2003) where the “neighbors” are identified using a contiguity measure. The inclusion of this spatial variable, neighborhood effect, into the growth regression model, conforms to the spatial auto-regressive model discussed by Anselin (1988).

The negative and significant effect of the neighborhood variable in the regression model signifies a negative spatial correlation among the neighboring provinces. As the average growth rate of per capita income of the neighbors increase, the average growth rate of per capita income in the home province decreases. This “beggar thy neighbor” phenomenon experienced by the provinces in the Philippines is highlighted in the case of the province of Cebu where the home province (Cebu) has a higher growth rate than the national average (3.21% vs. 1.86%), while its neighbors’ average income growth is lower than the national average (1.71% vs. 1.86%).

The education variable, measured by the number of years of schooling of the household head, is included in the model to measure human capital. However, the education coefficient (0.1483 for model 1), while positive, is not significant in explaining variations in the average provincial income growth in the Philippines. One possible explanation is that the education variable in the model was not able to capture very well the level of human capital in the provinces.

In model 2, two time-varying policy variables, infrastructure index and change in electricity, are included while the variables education and net migration are excluded. The six retained variables remain significant. The additional time-varying policy variables have positive signs, as expected. However, of the two, only the infrastructure index is a significant determinant of income growth, while improvement in the access to electricity is not. A 10 percentage points increase in infrastructure index, results to an increase of 0.17 percentage point (or 17 basis points) in the estimated average provincial per capita income, all things being the same.

Since some of the explanatory variables, particularly education and the proportion of young dependents, are not strictly exogenous variables, the models are estimated again, this time using instrumental variables in the regression. Columns four and five show the results of the model 1 specification, re-estimated using two stage least squares (model 3) and the generalized method of moments (model 4). These two estimation procedures are better than the ordinary least squares since they provide consistent estimates of the coefficients.

The coefficient of the proportion of young dependents is negative and significant for both procedures. Moreover, the magnitude of the coefficient is larger than that of the two previous models. This is one indication that the proportion of young dependents is a robust determinant of income growth.

III. ROBUSTNESS OF THE VARIABLES

The coefficients of the growth regression model were then subjected to diagnostic procedures known as the Extreme Bound Analysis (EBA) and Bayesian Averaging of Classical Estimates (BACE) to check whether the signs and magnitudes of the coefficients change depending on the presence of other explanatory variables in the model.

The two robustness procedures were performed under the assumptions that there are seven explanatory variables in the model (a typical number for growth regression) and with log of initial income (initial condition) and education (measure of human capital) always present in the models.

In testing for the robustness of the 14 explanatory variables defined, it is assumed that the logarithm of initial mean income (initial condition) and education (proxy for human capital) are always present in the model (12 variables remain in the pool). The number of explanatory variables for every model is pegged at 7, a typical number for a growth regression model. In the process, a total of 792 models were run, with each of the 12 variables in the pool appearing 330 times. The two fixed variables (initial condition and education) appear 792 times in the regression runs.

A. Extreme Bound Analysis

Table 2 presents the results of the extreme bound analysis. The determinants of income growth are presented in the first column while column two shows how many times a particular determinant is included in the 792 models. Columns three and four report the lower and upper extreme bounds, respectively, for all the fifteen variables of interest.

From the table, it shows that eleven out of the fifteen variables have lower extreme bounds which are negative and upper extreme bounds which are positive. This means that under the extreme bound analysis, only four can be considered as robust while the remaining eleven variables are non-robust. The four robust determinants of economic growth under this test is the log of initial income, the ARMM indicator, and the expenditure GINI and its square. Of the four robust determinants, only the expenditure GINI has a positive sign as reported in column five.

Table 2. Robustness of the Coefficients: Extreme Bound Analysis (EBA)

VARIABLE	n	Lower Extreme	Upper Extreme	SIGN	Significant Models count	Significant Models %	Remark
Log of initial income	792	-4.58	-1.04	-	792	100	Robust
ARMM indicator	330	-5.77	-0.37	-	330	100	Robust
Expenditure GINI	330	2.92	113.79	+	330	100	Robust
Square of expenditure GINI	330	-154.73	-9.32	-	330	100	Robust
Proportion of young dependents	330	-0.18	0.03	-	242	73.33	Not robust
Net migration	330	-0.03	0.01	-	225	68.18	Not robust

Landlock	330	-0.28	1.32	-	180	54.55	Not robust
Education	792	-0.32	0.86	+	299	37.75	Not robust
Change in electricity	330	-0.01	0.04	+	87	26.36	Not robust
Typhoon	330	-0.57	1.65	+	87	26.36	Not robust
Neighborhood effect	330	-0.89	0.58	-	85	25.76	Not robust
Infrastructure index	330	-1.36	3.85	+	38	11.52	Not robust
Change in road	330	-5.22	5.86	-	16	4.85	Not robust
Change in CARP	330	-4.43	4.05	+	10	3.03	Not robust
Mortality rate	330	-4.15	3.85		0	0	Not robust

B. Bayesian Averaging of Classical Estimates

The results for the Bayesian averaging of classical estimates are presented in table 3. The determinants of income growth are listed in column 1, while the means and standard errors of the coefficients computed from all the models, are given in columns 2 and 3, respectively. The fourth column provides the sign certainty probability, or the probability that the estimated coefficient is on one side of zero (positive or negative).

As from the previous procedure, the log of initial income, the ARMM indicator, and the expenditure GINI and its square, stand out as robust income growth determinants. While the log of initial income and ARMM indicator have a sign certainty probability of 1.00, the expenditure GINI and its square have a sign certainty probability of 0.99. Besides these four variables, the BACE produces another robust determinant of income growth. From this procedure, it is concluded that the proportion of young dependents is strongly correlated with income growth with a certainty probability of 0.99.

Furthermore, net migration and neighborhood effect are considered marginally robust with both having a sign certainty probability of 0.97.

**Table 3. Robustness of the Coefficients:
Bayesian Averaging of Classical Estimates (BACE)**

VARIABLE	Mean Beta	Mean Standard Error	Sign Certainty Probability (one side of 0/ + or -)	Remark
Log of initial income	-2.81	0.288	1	robust
ARMM Indicator	-2.15	0.629	1	robust
Proportion of young dependents	-0.09	0.001	0.99	robust
Expenditure GINI	43.76	397.215	0.99	robust
Square of expenditure GINI	-65.21	719.225	0.99	robust

Neighborhood effect	-0.36	0.038	0.97	marginal
Net migration	-0.01	0.00003	0.97	marginal
Landlock	0.42	0.094	0.91	not robust
Infrastructure index	1.21	1.001	0.89	not robust
Change in CARP	-1.12	1.194	0.85	not robust
Change in electricity	0.01	0.0001	0.84	not robust
Education	0.16	0.031	0.82	not robust
Typhoon	0.29	0.159	0.77	not robust
Change in road	0.25	0.942	0.6	not robust
Mortality rate	0.15	1.500	0.45	not robust

The rest of the variables show little evidence of robust partial correlation with income growth using the empirical test. These variables that are considered as weak determinants are education, change in CARP, change in the proportion of households with electricity, change in the quality of roads, infrastructure index, the indicator variable landlock, mortality rate, and the number of typhoons. It is important to note that from the previous test, the landlock indicator was found to be marginally robust.

IV. CONCLUSIONS

A central question for empirical economics, particularly economic growth, is which explanatory variables to include and exclude in the regressions. This paper aims to identify variables strongly correlated with growth applying three robustness procedures in determining which variables are strongly correlated with income growth.

The extreme bound analysis (EBA) and Bayesian averaging of classical estimates (BACE) were applied to fifteen explanatory variables from a data set consisting of 74 Philippine provinces for the period 1985 to 2003. These explanatory variables which are considered to be determinants of income growth comprise of a set representing initial economic, demographic and institutional conditions, a set of time-varying policy variables and neighborhood effects.

From these tests, four variables stand out as being robust. The log of initial income, the ARMM indicator, and the expenditure GINI and its square are all considered as strongly correlated to growth.

Also, the proportion of young dependents is shown to be strongly correlated with income growth under the BACE. Marginally robust determinants under BACE include net migration, landlock, and neighborhood effect.

The remaining variables show little evidence of robust partial correlation with income growth using the empirical test. These variables that are considered as weak determinants are education, change in CARP, change in the proportion of households with electricity, change in the quality of roads, infrastructure index, the indicator variable landlock, mortality rate, and the number of typhoons.

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