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BIAS CORRECTION IN A DYNAMIC PANEL DATA MODEL OF ECONOMIC GROWTH: THE AFRICAN DUMMY RE-EXAMINED

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ABSTRACT

The discrepancy between the observed and expected growth rates of African economies in cross-country or panel growth regressions is often summarised in a significant African dummy. However, the existence of this dummy may be an artifact of the panel data techniques used. The standard LSDV (least squares dummy variable) method produces a large bias in the estimate of the coefficient on the lagged dependent variable, which could generate the observed African dummy. The lagged dependent variable in a growth model is used to calculate the cross-country rate of convergence. If, however, the convergence rate is overestimated, then the Africa dummy would result due to the clustering of African economies at the lower end of the world cross-country income distribution. Correcting for the bias - using Kiviet's (1995) algorithm - allows a fresh look at the apparent systematic underperformance of African countries relative to their growth predictions. Little evidence remains of such underperformance by African economies once the relevant bias in the dynamic panel has been accounted for.

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1. INTRODUCTION

Errors of measurement are not invariably unproductive: It is, as Lord Acton remarked, to Columbus' "…auspicious persistency in error [that] Americans owe, among other things, their existence" (Acton, 1921: 61). The thesis of this paper is that growth economist may have misjudged the impact of regional effects due to a measurement error - especially where the significant and negative African dummy in the empirical growth literature of recent vintage[i] is concerned. This too, may have been a productive mistake, promoting creative conjectures regarding socio-political, geographic and economic forces that may have contributed to Africa's economic decline[ii]. Hopefully, the more accurate estimate of the African dummy suggested here might contribute to a refocusing of economists' attention on the systematic factors underlying economic growth internationally as much as it improves our understanding of problems peculiar to African economies.

Earlier empirical research on cross-country economic growth, including those investigating African underperformance, was typically based on cross-sectional regressions[iii]. Recently the combination of access to large relevant panel data sets, user-friendly computer packages and the increased awareness of the shortcomings of cross-sectional regressions have encouraged research employing a variety of panel data models.

However, dynamic panel regressions are plagued by formidable problems, particularly the systematic bias in the estimator of the coefficient on the lagged dependent variable (γ hereafter), first identified by Nickell (1981). Monte Carlo studies have shown this bias to be significant and large (Judson and Owen, 1996). As growth models are inherently dynamic, this bias is directly relevant to empirical growth research. The lagged dependent variable in a growth model is used to calculate the cross-country rate of convergence. Consequently, biased estimates in dynamic panels are not only of technical concern, but affect one of the central empirical issues – the estimated rate of convergence – directly.

Further, the bias in the convergence term leads to a bias in other coefficients of the model. This is an important issue, since the size and significance of the African dummy may, to a large degree, be an artefact of the biased panel method employed. In this paper Kiviet's (1995) bias correction method is used to correct for the biased parameter estimates in dynamic panels. This allows a fresh look at the issue of African economic underperformance within the general framework of the Solow growth model.

2. PANEL DATA ESTIMATION METHODS

Pesaran and Smith (1995) identify four methods for identifying the average long-run effect of exogenous variables in a panel regression, they are: mean group estimation, fixed or random effects, group averages, and pooled data estimation. The choice between the four methods is not a matter of indifference except when the data satisfies very restrictive conditions that are atypical for macroeconomic panels. The fixed effects method used in the present investigation corresponds with much of the growth literature [for example Hoeffler (2000) and Islam (1995)]. Nevertheless, the fixed effects method is not used universally - Nerlove (1996), for example, uses various random effects models.

The decision between a fixed effects model or a random effects model is important in the growth literature (Nickell 1981: 1417). This question is particularly relevant if the number of countries in the panel is large relative to the panel's time dimension, as a fixed effects model introduces a large number of country dummies, reducing the degrees of freedom. Furthermore, if the country dummies of the fixed effects model are not subsequently analysed, useful information may be lost. These arguments could prejudice the model design in favour of random effects models as opposed to a fixed effects model. However, it is highly likely that these country-specific characteristics are correlated with other variables if country effects represent omitted variables. In that case Nickell (1981: 1418) argues that one is "lead inexorably to the fixed effects model" as the country dummies may reduce the bias created by omitted variables. More recently, Judson and Owen (1996: 1) argued that: "…[the] use of panel data in estimating common relationships across countries is particularly appropriate because it allows the identification of country-specific effects that control for missing or unobservable variables."

Besides the loss of degrees of freedom and potential loss of useful information, the significantly biased results of standard estimations techniques is a serious disadvantage in the use of the fixed effects model[iv]) Monte Carlo simulations have confirmed that the bias produced by the standard Least Square Dummy Variable (LSDV) estimator for fixed effects models is indeed significant and large [for example: Cermeno (1999), Kiviet (1995), Judson and Owen (1996)].

In order to address this bias, alternative consistent estimators have been developed in the literature. Anderson and Hsiao (1981) have, for example, proposed two instrumental variables methods. They suggested that either the two-period lagged difference of the dependent variable or the two-period lagged level of the dependent variable be used as instruments as both instruments would lead to a consistent (though still biased in finite samples) estimator (Adam, 1998: 5). Subsequent Monte Carlo simulations have indicated that using the lagged difference as an instrument will result in a very large variance and in general, using the lagged levels as instrument is superior (Arellano and Bond 1991, Kiviet 1995). This second of Anderson and Hsiao's instrumental variable techniques will be called the AH_IV hereafter.

Arellano and Bond (1991) have suggested that significant efficiency gains may be achieved by using additional instruments, leading to a so-called Generalized Methods of Moments (GMM) estimator[v]. Hoeffler (2000) also introduced a systems GMM estimator as an alternative.

Whereas the AH and GMM techniques specify consistent estimators for the lagged dependent variable in a dynamic panel, Kiviet (1995) suggested an alternative strategy according to which the biased LSDV estimator is adjusted in a two-step procedure. The merit of Kiviet's (1995) strategy is in the relatively low standard deviation of the LSDV estimator. However, in order to estimate the bias, the residuals from a first-step consistent estimator, such as the AH_IV, are needed. This leads to the following two-step procedure:

1. Use a consistent estimator such as the Anderson-Hsiao's instrumental variable method to estimate the residuals of a consistent estimator. The (biased) LSDV coefficients are also estimated.
2. Use the residuals calculated in step 1 to correct the biased LSDV coefficients using Kiviet's (1995) bias correction formula.

A growing literature, including Bun and Kiviet (1999), Cermeno (1999), Judson and Owen (1996) and Kiviet (1995) tests the relative merit of these strategies empirically, using Monte Carlo techniques.

In general (except for OLS) the bias of the lagged dependent variable effect, γ, is more significant than the bias on other effects in the dynamic panel. Whereas LSDV leads to a severely biased estimate in typical macroeconomic applications, the extent of this bias depends on the size and composition of the data set. As predicted by Nickell (1981), the bias of the LSDV increases with γ - the true coefficient of the lagged dependent variable - and decreases as the time dimension becomes larger (Judson and Owen, 1996: 7). Indeed, all the estimators (except OLS) improve as the time dimension increases.

For the purpose of the growth regression in the second part of this paper, we are particularly interested in the behaviour of the estimators for small time dimensions, say between 5 and 10 observations, and a relatively high γ, as the growth literature has so far indicated that the estimated effect of the latter lies between 0.77 and 0.97 [Islam (1995), Hoeffler (1998)].

Judson and Owen (1996) evaluate their Monte Carlo simulations for various cross-sectional and time dimensions and for γ=0.2 and γ=0.8. They confirm that the bias created by the LSDV estimator on γ is large, amounting to between 30% and 50% for time panels shorter than 10 (Judson and Owen, 1996: 7). Nevertheless, the LSDV estimator does have an important advantage in the form of its relatively small standard deviation. As a result, LSDV produces more efficient estimates than either the IV or GMM methods. Although the standard deviation of the corrected LSDV exceeds that of the uncorrected LSDV somewhat, the corrected LSDV (LSDVc hereafter) still appears to lead to more efficient estimates than either the IV or the GMM methods. Conversely, the AH_IV estimator produces the lowest average bias though at the costs of a large standard deviation[vi]. In turn, the GMM estimator (using two lagged values as instruments) shows the most significant improvement in the bias as the time dimension increases (Judson and Owen, 1996: 10-12).

The choice between estimators is a complex one, evidently depending on the composition of the panel. Nevertheless, the GMM estimator does not outperform the rivals considered here either in terms of the average size of bias or in terms of efficiency. Based on their Monte Carlo results, Johnson and Owen (1996: 12) suggest using the corrected LSDV for panels with small time dimension ($T \leq 10$) while recommending the AH_IV estimator for longer panels, as the efficiency of the IV estimator improves with T and the IV estimator is computationally simpler than the corrected LSDV.

As mentioned above, the present study is specifically interested in the performance of estimators when the time dimension is less than 10 and γ lies roughly between 0.8 and 1. This is also consistent with the high degree of persistence (high γ) observed in the dynamics of many macroeconomic panels (Cermeno, 1999: 4). While Judson and Owen (1996), Kiviet (1995) and Bun and Kiviet (1998) perform the Monte Carlo simulations for values of γ only up to 0.8, Cermeno undertakes a similar Monte Carlo study for γ values as high as 0.85, 0.95 and 0.99. In general, all of the estimators are expected to perform poorly as γ approaches one.

As mentioned above, the bias of the LSDV estimator is dependent on, and increasing in, γ. Consequently, the use of the uncorrected LSDV becomes even less desirable when γ is high. The IV estimator performs poorly, too[vii]. To the extent that the corrected LSDV relies on a consistent estimator, such as the IV, to calculate the bias, the performance of the corrected LSDV is also likely to deteriorate for high γ.

The simulation results for a sample of 100 countries (N=100) and time dimension of 5 (T=5) confirmed that the bias of the LSDV estimator – and to a certain extent also that of the corrected LSDV – increases with γ. While the AH_IV estimator has the smallest bias, it has the largest variance compared with the other estimators and becomes extremely imprecise at large γ values (Cermeno 1999: 7). As a result, the mean squared error of the AH_IV estimator exceeds that of the GMM and LSDVc estimators for a γ of 0.85 and greater. For γ between 0.5 and 0.85, the GMM1 and GMM2 estimators show a smaller bias, but larger standard deviation than the LSDVc estimator. Accordingly, the mean squared error of LSDVc compares favourably to that of the GMM estimators. However, for values of γ closer to one the mean squared error of the LSDVc is far superior to the GMM and AH_IV estimators as the LSDVc estimator shows the smallest bias as well as standard deviation (Cermeno, 1999: 8).

It appears that for the panel data dimension of many macroeconomic panel studies (T less than 10 and N as large as 100), the LSDVc seems worth investigating, though the remaining bias should be taken seriously and encourages caution in applying and interpreting dynamic macroeconomic panels[viii].

3. THE SOLOW MODEL

Empirical growth research is often somewhat *ad hoc* with cross-country regressions not necessarily derived rigorously from a model (Hoeffler, 2000: 10). However, the neo-classical (Solow) growth model provides a theoretical framework within which to analyse cross-country differences in the level of GDP per capita as well as variations in growth rates in output per capita. After nearly fifty years, it remains a useful and popular model on which to base empirical growth research[ix].

The Solow model is built around a Cobb-Douglas aggregate production function with an assumption of diminishing returns for each factor of production individually, but constant returns for all factors jointly. The factors of production are capital (*K*), labour (*L*), and labour-augmenting technology (*A*). Production at time *t* is given by

$$Y_t = K_t^{\alpha}\left[A_t L_t\right]^{1-\alpha} \qquad (1)$$
$$0 < \alpha < 1$$

L and *A* are assumed to grow exogenously at constant rates of *n* and *g* respectively. Effective labour, A_tL_t, therefore, grows at a rate of $n+g$. It is assumed that a constant percentage of output, *s*, is invested while capital depreciates at a rate of δ. It can be shown that a steady-state output per worker exists, such that

$$\ln\left(\frac{Y}{L}\right)^{*} = \left(\frac{\alpha}{1-\alpha}\right)\left(\ln s - \ln\left(n+g+\delta\right)\right) + \ln A_0 + gt \qquad (2)$$

While an increase in the savings rate, s, and in technology, A_0, raises the steady-state, the population growth rate, n, enters the steady-state equation negatively. The steady state is globally stable and the transitional dynamics towards this steady state can also be derived in the neighbourhood thereof. Accordingly the *growth rate* in output per labour is given by the expression in (3)

$$\ln\left(\frac{Y_t}{L_t}\right) - \ln\left(\frac{Y_0}{L_0}\right) = -\left(1-e^{-\lambda t}\right)\times\ln\left(\frac{Y_0}{L_0}\right)$$
$$+\left(1-e^{-\lambda t}\right)\times\frac{\alpha}{1-\alpha}\times\ln\left(s\right) - \left(1-e^{-\lambda t}\right)\times\frac{\alpha}{1-\alpha}\times\ln\left(n+g+\delta\right) \qquad (3)$$
$$+\left(1-e^{-\lambda t}\right)\times\ln\left(A_0\right) + gt$$

where $\lambda = (1-\alpha)(n+g+\delta)$ is the rate of convergence.

For a given initial output per labour, a higher steady-state implies a faster transitional growth rate and hence s and A_0 enter equation (3) positively while *n* enters negatively. The initial output per labour is negatively correlated with the growth rate due to the diminishing returns assumed in the model. This is generally referred to as the convergence effect, predicting catch-up growth for initially poor countries. Further, *g* enters equation (3) positively and once the steady-state output per labour is reached, ln*(Y/L)* will grow only at a rate of *g* for a given ln*(Y/L)**.

While the dependent variable is specified in terms of a growth rate and the dynamic nature of the model is somewhat disguised in equation (3), a simple manipulation yields the expression in equation (4) below.

$$\ln\left(\frac{Y_t}{L_t}\right)=e^{-\lambda t}\ln\left(\frac{Y_0}{L_0}\right)+\left(1-e^{-\lambda t}\right)\times\frac{\alpha}{1-\alpha}\times\ln(s)$$
$$-\left(1-e^{-\lambda t}\right)\times\frac{\alpha}{1-\alpha}\times\ln(n+g+\delta)+\left(1-e^{-\lambda t}\right)\times\ln(A_0)+gt \qquad (4)$$

The dependent variable is now the level of per capita GDP and the dynamic aspect of the model is apparent from the lagged dependent variable. The equation is now in the form of a dynamic panel with the fixed effects accounting for the unobserved $\ln A_0$ term (as well as any other country-specific factor omitted from the regression). While one of the first panel studies in the growth literature used LSDV (Islam, 1995) to estimate (4), subsequent studies have employed more sophisticated econometric techniques, for example Hoeffler (2000) applied the GMM and IV estimation method while Nerlove (2001) used a number of different random effects models.

4. EMPIRICAL RESULTS

The data set was constructed from the Penn World Tables version 5.6, including GDP per capita, investment and population data and is described in Appendix 1. The goal of the empirical section is to compare the results obtained using LSDV and the (Kiviet) corrected LSDV for a growth analysis based on the Solow model.

(a) Results

Table 1 reports the results for the (uncorrected) LSDV estimation method. All variables are significant and have the expected signs.

Table 1. Uncorrected LSDV estimation

Dependent Variable: $\text{Log}(GDP/L_t)-\log(GDP/L_{t-1})$		
	Coefficient	t-statistic
$\text{Log}(GDP/L_{t-1})$	-0.262	26.68
Log(I/GDP)	0.213	6.631
Log(n+0.05)	-0.074	-2.377

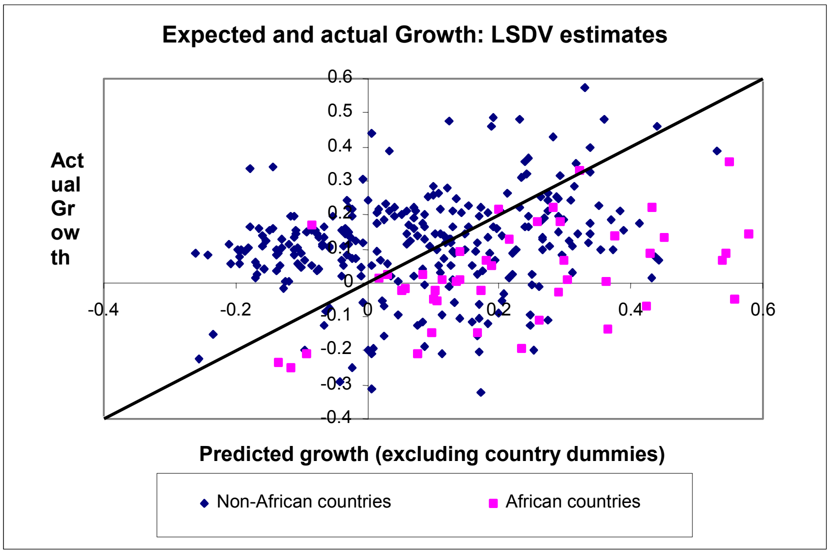
Table 2. Average Investment and Savings rates

	Sub-Saharan Africa countries	Non-African countries
Average investment rate	11.1%	20.2%
Average population growth rate	2.6%	1.6%

Table 2 indicates that on average, African countries have a lower savings rate and higher population growth rate than the non-African countries in the data set. From equation (3) it should be clear that these features should diminish the steady state output per worker in Africa relative to those countries with lower population growth and higher savings rates. This is consistent with Collier and Gunning's (1999: 65) observation that "Africa's slow growth is thus partly explicable in terms of particular variables that are globally important for the growth process, but are low in Africa". Therefore, the surprising aspect of growth regressions like those in Table 1 is that they predict faster than average growth for African countries due to the convergence effect. This prediction is shown graphically in figure 1 where the African countries are clustered on the positive part of the axis measuring predicted growth.

History did not bear out this optimistic conditional forecast for African economic growth. The disparity between the actual and predicted growth performance is seen in the clustering of African countries below the actual versus fitted diagonal in figure 1. In general, more than a third of the observations of African countries lie in the lower right quadrant, indicating negative growth in GDP per capita while the model predicted positive growth rates. This result holds for the average experience of sub-Saharan Africa, and does not deny the exceptional performances if countries like Botswana. Given the output in figure 1, it is not surprising that an Africa dummy is significant in a model like that of Table 1.

Figure 1



The usual response in the literature has been to try and explain the African dummy. This has lead to much fruitful research, but may have distracted the attention from some other features of the poor economic performance in Africa, like the continent's low investment rate, capital flight and so on.

There is, however, another potential explanation for the mismatch between actual and predicted growth in Africa, which is also clear from table 1, that is: African countries are clustered at the poorer end of the world's cross-country income distribution. Together with the high rate of convergence (estimated at 6% per annum, for the LSDV estimated model) this clustering of poor African countries would naturally lead to the high expected growth rates from these countries, as observed in figure 1. If the convergence rate had been overestimated though, then the Africa dummy observed in figure 1 could be the result of this estimation bias.

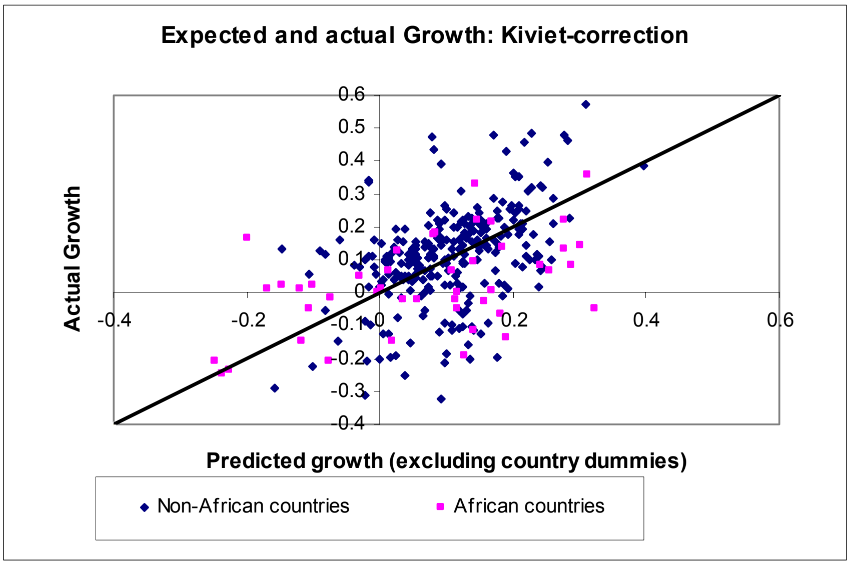
The results of the estimated bias and the Kiviet-corrected LSDV estimates are presented in Table 3. As the LSDV estimator leads to a downward bias on the coefficient of Log(GDP/Lt-1) and the speed of convergence is inversely proportional to the relative size of this coefficient, the LSDV estimator overstates the true speed of convergence. Once the Kiviet correction is applied, the implied speed of convergence declines from 6% for the LSDV estimates to 2.6%. These estimates are similar to the ones of Hoeffler (2000: 49) who records a speed of convergence of 5.1% for the LSDV regression and between 2.1% and 3.2% when various GMM estimators are used[x]. While the coefficient of the initial output per worker seems to show the most severe bias, the estimates of the other parameters were also biased.

Table 3. Estimated bias and corrected LSDV estimation

Dependent Variable: Log(GDP/L_t)-log(GDP/L_{t-1})			
	LSDV	Estimated Bias	Corrected LSDV
Log(GDP/L_{t-1})	-0.262	-0.139	-0.122
Log(I/GDP)	0.213	0.008	0.205
Log(n+0.05)	-0.074	-0.006	-0.068
Speed of convergence λ	6%		2.6%

Once we correct for the bias in the LSDV estimation (figure 2), two important changes are observed. Firstly, African countries are no longer expected to grow faster than countries elsewhere and secondly, the systematic disparity between the actual and predicted growth performance of African countries seems to have disappeared as roughly 40% of the observations of African countries lie either on or above the diagonal. African countries no longer seem to show a systematically different experience when examined with the Solow model[xi], and the African dummy may have been an artefact of the statistical methods employed.

Figure 2



To quantify the impact of the LSDV correction on the African dummy a second stage has been added to the regression analysis. This is necessary as the African dummy is a linear combination of the country dummies, and hence we cannot include the latter (to make provision for the fixed effects) while also including an African dummy. The extension uses the estimated β coefficients of Table 2 to construct a new variable mainly representing slow changing or country-specific fixed effects plus the residuals for the LSDV and the corrected LSDV estimator respectively. This is done by subtracting the explained variation in growth – excluding the fixed country effects – from the dependent variable as shown in equation (5).

$$\left\{\ln\frac{Y(t_2)}{L(t_2)}-\ln\frac{Y(t_1)}{L(t_1)}\right\}-\left\{\alpha+\beta_1\ln\frac{Y(t_1)}{L(t_1)}+\beta_2\ln s+\beta_3\ln(n+0.05)\right\} \quad (5)$$
$$=v_t+\varepsilon_{i,t}$$

The newly constructed variable - which represents everything unexplained by the Solow model - is now used as a dependent variable in a regression with the African dummy as explanatory variable.

Using the LSDV estimator, we find a negative African dummy significant at the 1% level. While an Africa dummy is still present once the Kiviet-correction is applied, the size of the coefficient drops to roughly a fifth of its previous biased estimate and its significance is reduced to the 5% level. Furthermore - when using the LSDV estimator - 15% of the variance in unexplained growth seems to be attributable to African countries. This is significantly reduced once we adjust for the bias and the remaining errors are less systematic, at least with regard to the Africa experience. These results are reported in Table 4.

Table 4. Size and significance of African dummy

Dependent Variable: Growth unaccounted for after adjusting for differences in initial GDP, savings rate and population growth rate				
	v+e	v+e (Kiviet)	v+e	v+e (Kiviet)
African dummy	-0.234***	-0.048**	-0.11***	-0.03
(t-statistic)	(-7.650)	(-2.232)	(-4.190)	(-1.2)
Open			0.05**	0.07***
			(2.153)	(3.27)
Ln(education)			0 .14***	-0.06
			(2.972)	(-1.4)
Institution			0.38***	0.12**
			(7.33)	(2.4)
R^2	0.15	0.01	0.38	0.04

The asterix indicates significance at 1% (***), 5% (**) and 10% (*) respectively.

A fairly standard extension of the Solow model broadens the scope of capital to include human capital as per Mankiw Romer and Weil's (1992) influential paper. Sachs and Warner (for example, 1997) have also made the inclusion of an openness variable in growth regressions non-controversial. To these two standard extensions of the Solow model we add a slightly more controversial variable measuring the institutional quality in countries[xii].

The fixed effects and residuals of the models in tables 1 and 2 were then regressed on these additional variables. The results are interesting and reported in the final two columns of table 4. In the regression based on the corrected LSDV estimator coefficients the African dummy is no longer significant. In contrast, the Africa dummy remains significant at the 1% level in the model estimated with standard LSDV.

These results indicate that if no provision is made for the bias inherent in a dynamic panel data, the African dummy is appreciably overestimated. Further, the failure of other regressors to account for the African dummy using the LSDV coefficients indicates the potential distortion caused by this measurement error. Whereas the literature has, to an extent, been wrestling with explaining an overstated African dummy, the modest actual African dummy is easily explained. With the African dummy accounted for, attention can be directed to understanding other factors that causes Africa's low steady state, like a low rate of investment.

5. CONCLUSION

African economic performance has been poor and according to many of the empirical growth models it has been inexplicably so. A significant and negative African dummy summarises the problem. However, observing a significant African dummy could follow from either of two potential causes: first, there is something systematically debilitating in African economies which causes a worse than average experience, other things equal. Second, the known downward bias of the lagged dependent variable in dynamic panel (like those used in the recent growth literature) could cause the same observation since African economies tend to be clustered at the poorer end of the world income distribution and their expected rate of convergence is, consequently, likely to be overstated.

This paper implemented Kiviet's (1995) LSDV correction for a dynamic panel and argues for the second of these possible explanations of the African dummy. The results suggest that biased coefficients in the growth model largely explain the African dummy. Further, what remains of the African dummy can be accounted for by standard extensions of the Solow model; a result not obtained when the analysis is repeated with the uncorrected LSDV estimator.

As a technical issue the bias in dynamic panels matters. In practise, it matters too, as it distorts the coefficients in empirical growth models, leading to an overestimation of the rate of cross-country convergence and so overstating the Africa dummy in size and significance. This African dummy risks distracting our attention from those issues – like the rate of investment – which matter for growth here, as elsewhere.

APPENDIX 1

(a) Data

A balanced panel is required for the implementation of the Kiviet correction, as the algorithm used cannot accommodate gaps in the data[xiii]. Since we will also be interested in how the African dummy relates to the relative level of education, institutional quality and openness in Africa, these data requirements reduce the number of countries in our dataset to 63 of which 9 are located in sub-Saharan Africa.

The time period under consideration is 1965 to 1990. While data is available for 1960, the data for that year is used as an instrument in the analysis. The 25-year period is divided into five-year intervals giving a panel with 6 time observations.

Due to a lack of further information of the depreciation rate and the exogenous rate of technological progress, it is common in the growth literature to set $\delta+g$ equal to 0.05 for all countries and time periods[xiv]. Furthermore, this ensures that $(n+g+d)$ takes on a positive value and $\ln(n+g+d)$ is defined for all countries.

Table 5 Countries included in the data set

ARGENTINA	HONDURAS	PAPUA N.GUINEA
AUSTRALIA	HONG KONG	PARAGUAY
AUSTRIA	INDIA	PERU
BANGLADESH	IRELAND	PHILIPPINES
BELGIUM	ISRAEL	PORTUGAL
BOLIVIA	ITALY	SENEGAL
BRAZIL	JAMAICA	SINGAPORE

CAMEROON	JAPAN	SOUTH AFRICA
CANADA	JORDAN	SPAIN
CHILE	KENYA	SRI LANKA
COLOMBIA	KOREA, REP.	SWEDEN
COSTA RICA	MALAWI	SWITZERLAND
DOMINICAN REP.	MALAYSIA	SYRIA
ECUADOR	MEXICO	TRINIDAD&TOBAGO
EL SALVADOR	MOZAMBIQUE	TUNISIA
FINLAND	NETHERLANDS	TURKEY
FRANCE	NEW ZEALAND	U.K.
GERMANY, WEST	NICARAGUA	U.S.A.
GHANA	NORWAY	UGANDA
GREECE	PAKISTAN	URUGUAY
GUATEMALA	PANAMA	ZIMBABWE

The data series used in the growth models are described in table 6.

Table 6

Abbreviation	Description	Source
GDP/L	Real GDP per capita	PWT, 5.6
I/GDP	Real investment share of GDP measured in 985 international prices (I/GDP$_{1965}$ is the average investment rate for the period 1961 through 1965)	PWT, 5.6
n	Population growth rate overt he preceding five years expressed as an effective annual rate	PWT, 5.6
Open	Five year average of Sachs and Warner's (1995) binary openness indicator.	Sachs and Warner's (1995)
Education	Log of the average schooling years in the total population.	Barro and Lee (2000)

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[i] The Africa dummy suggests that after controlling for the usual components of a growth model - the savings rate, population growth rate and perhaps some extensions like human capital – there is an unobserved and significantly negative factor, shared by Sub-Saharan African countries on average, which inhibits the growth of these countries.

[ii] For example, Collier and Gunning (1999), Hoeffler (2000) and Sachs and Warner (1997).

[iii] Mankiw, Romer and Weil (1992) and Sala-i-Martin (1997) are examples.

[iv] In the fixed effects model the lagged dependent variable is positively correlated with the time-invariant country effect. This leads to a downward bias in the estimated coefficient of the lagged dependent variable (Hoeffler, 2000: 8)

[v] Cermeno (1996: 6) distinguishes between two versions of GMM estimators. GMM1 is a generalisation of the AH_IV estimator, including all lags of the dependent variable as instruments. GMM2 uses the estimated differenced residuals from the GMM1 results to generate the co-variance matrix in a two-step procedure.

[vi] Indeed, due to the high standard deviation the likelihood that a "bad draw" would result in an estimate far from the actual value is increased (Judson and Owen 1996: 12)

[vii] As γ increases and the dependent variable approaches a random walk, the lagged values of the dependent variable become inferior instruments as they are less correlated with the dependent variable.

[viii] One significant drawback of the LSDVc strategy is that it cannot be implemented for unbalanced panels. Therefore, countries with incomplete data have to be purged from the data set. Consequently, the coverage and representativeness of the sample should also be considered when deciding on an estimation technique in this context.

[ix] Recent studies using the Solow model include Islam (1995), Temple (1999), Hoeffler (2000), and Nerlove (2001).

[x] Temple (1999: 133-134) summarises the convergence literature and mentions that 2% is a fairly typical result in cross-country growth regressions. The convergence rate in studies using panel data have been more varied though, ranging from 0 to 30% per annum.

[xi] This is, of course, an empirical question. Accordingly, the African dummy is re-examine in section 4(b).

[xii] We used Knack and Keefer's (1995) institutional quality index.

[xiii] Adam (1998) published an algorithm to calculate the LSDVc estimator using Stata. His algorithm was implement here.

[xiv] See for example, Hoeffler (2000: 18)