

The Africa-Dummy: Gone with the Millennium?

Max Köhler*, Stefan Sperlich†

DP version 2014/15

Abstract

A fixed effects regression estimator is introduced that can directly identify and estimate the Africa-Dummy in one regression step so that its correct standard errors as well as correlations to other coefficients can easily be estimated. We can estimate the Nickel bias and found it to be negligibly tiny. Semiparametric extensions check whether the Africa-Dummy is simply a result of misspecification of the functional form. In particular, we show that the returns to growth factors are different for Sub-Saharan African countries compared to the rest of the world. For example, returns to population growth are positive and beta-convergence is faster. When extending the model to identify the development of the Africa-Dummy over time we see that it has been changing dramatically over time and that the punishment for Sub-Saharan African countries has been decreasing incrementally to reach insignificance around the turn of the millennium.¹

Keywords: Africa dummy, panel econometrics, poverty and development, growth economics
JEL code: C01, C23, C51, O11, O47

*University of Göttingen, Courant Research Center for Poverty, Equity and Growth, Göttingen, Germany

†Corresponding author: Université de Genève, Switzerland, stefan.sperlich@unige.ch

¹We acknowledge helpful discussion and comments from Inmaculada Martinez-Zarzoso, Jacques Silber, Stephan Klasen, and Thomas Kneib as well as some help with data preparation by Julian Vortmeyer.

1 Introduction

To study the Africa-Dummy we start out from the classical growth model of [Mankiw, Romer and Weil \(1992\)](#). This model contains several simplifications; most countries possess certain characteristics that are hard to measure and to incorporate but represent systematic drivers for growth like for example international capital markets ([Barro, Mankiw and Sala-i-Martin \(1995\)](#)). [Islam \(1995\)](#) criticized that countries have fundamentally differing production functions so that comparisons between their economies are difficult. A further simplification is the assumption that the endowment with resources can be infinitely substituted by capital. [Georgescu-Roegen \(1975\)](#) argue that this point of view is too optimistic with respect to the limitations of technological progress. Other variables that are correlated to economic growth but not incorporated in the growth model are political factors (see [Collier and Gunning \(1999\)](#)), diseases like AIDS (see [Were and Nafula \(2003\)](#)), geographical factors and trade openness (see [Sachs and Warner \(1997\)](#)), ethnic diversity (see [Easterly and Levine \(1997\)](#)) or historical background such as the colonial heritage (see [Price \(2003\)](#)), to mention a few. Among others, these problems result in empirical weaknesses. Among others, [Barossi-Filho, Goncalves Silva and Martins Diniz \(2005\)](#) summarize that among most regressions the estimated capital share exceeds the value obtained from the national accounts and that the estimated convergence rate is usually too low. One example is the group of sub-Saharan African countries, meaning that the model by [Mankiw, Romer and Weil \(1992\)](#) is not able to explain the growth in sub-Saharan Africa, because its economic fundamentals incorporated in the model are not as bad as their actual performance. The result is that, if an additional variable is added, that only indicates the membership to sub-Saharan Africa, namely the Africa Dummy, it has a significant coefficient with a negative sign. As African countries started with a lower level of income, they should converge to the income observed in regions that have similar characteristics. The presence of a negative Africa-Dummy indicates that this might not be the case.

However, although several of the above mentioned papers seem to have succeeded in explaining the reasons for the Africa-Dummy, they did so by quite - if not completely - different arguments, respectively its corresponding variables. In fact, adding variables to the growth regression in order to explain the Africa-Dummy is critical. In almost all these cases these additionally included variables just identified almost uniquely the belonging of a country to Sub-Saharan Africa, and therefore act just like the Africa-Dummy. For example [Levine and Renelt \(1992\)](#) test the causality of different explanatory variables in growth regressions. They summarize that most of the included variables are not robust and depend on the model. [Collier and Gunning \(1999\)](#) note that this adding of explanatory variables transfers the puzzle elsewhere. Moreover, many explanatory variables that are added in growth regressions do not necessarily identify drivers for growth. Instead, they are somehow correlated to what is not explained by the growth model but - like here - just identify a geographical region. Finally, many country specific characteristics are time invariant so that they have already been accounted for in fixed effect panel models.

The naive way in which explanatory variables are added or deleted from growth models motivates to only use the explanatory variables given by [Mankiw, Romer and Weil \(1992\)](#) and to accept that growth for (Sub-Saharan) Africa is different. First we discuss how to

identify and estimate the Africa-Dummy. When [Hoeffler \(2002\)](#) tried to address this problem she found that the significance of the Africa-Dummy disappeared when applying a two step system GMM. We will briefly discuss the advantages of our approach over two-step procedures and some of the disadvantages of the system GMM. We call our approach the Two-Groups Least-Square Dummy-Variable estimator. This method has the advantages that it is able to estimate the Africa-Dummy in one regression step, that it is consistent even if the residuals are autocorrelated, it is able to control for all fixed effects without the need of equal variances of the fixed effects, and it gives correct standard errors and correlations for all estimated coefficients. Estimating the coefficients of the growth model with the Two-Groups Least-Square Dummy-Variable estimator identifies a negative significant Africa-Dummy. The correlations of estimates tell us its relationship to the other returns. In fact, this punishment for Sub-Saharan African economies increases if the return to investment in physical capital decreases, if the return the depreciation rate increases or if the return to school attainment increases. We check that the Africa-Dummy is not a result of misspecification of the functional structure like nonlinearities or interactions. It does not disappear when applying a semiparametric extension of the Two-Groups Least-Square Dummy-Variable estimator. When adding interaction effects one can observe that Sub-Saharan Africa have had positive returns to population growth and faster convergence, so that the Africa-Dummy becomes even significantly positive. Based on our method we can also study the evolution of the Africa-Dummy over time. Assuming world-wide similar returns as in the original model, the main finding here is that the African countries have been catching up so that this dummy has become insignificant in the recent years.

The rest of the paper is organized as follows. We first report the data selection and preparation for our study. Afterward, in [Section 3](#) we dedicate one section to the introduction and discussion of modeling and the estimation method we propose. Note that this method can equally well be applied to identify and estimate any time invariant impact in fixed effect panel models but is not specific to the problem of studying the Africa-Dummy. All empirical findings are presented and interpreted in [Section 4](#). Finally, [Section 5](#) concludes.

2 Data Selection and Preparation for the Growth Model

The objective was to collect long time-series for as many countries as possible for which we can guarantee good data quality. The information sources for the empirical investigation are the Penn World Table 6.3 (PWT), World Bank's World Development indicators and [Barro and Lee \(2010\)](#). Except of population growth and human capital, all data come from the PWT. It collects a broad range of macroeconomic time-series for almost all countries published by [Heston, Summers and Aten \(2009\)](#). The beginning of a widespread availability is 1960. Most variables are published until 2007, so that observations are obtained for 48 periods. [Heston, Summers and Aten \(2009\)](#) introduced a country rating system based on the number of participations in worldwide benchmark surveys, the variation of the accessible data and the quality of the statistical methods applied. This results in a grading scheme from A to D with descending order in which a rating of D is regarded as too weak to be included for a reliable empirical analysis. Furthermore, we also excluded countries that

where separated in a sub-period, for example Germany and the countries of the Soviet Union. Their incorporation would have made it necessary to unify several countries to one country or to split one country in a given period in several countries. The loss of data quality when doing this is unclear. We ended up with a sample of complete time series of 81 countries over 48 years giving a total sample size of 3888.

The selection process might cause a sample selection bias as it results in an underrepresentation of African and, to some extent, Asian countries. Poor countries have weaker databases and are more likely to be excluded, but due to the inclusion of country fixed effects and the Africa-Dummy this can just slightly affect the slopes of the within variation. If this within variation is somewhat different for the under- vs the overrepresented country groups, then there is no bias when applying our semiparametric methods which allow for flexible functional forms. Moreover, it is clear that in our model with interactions the potential bias due to an underrepresentation of African countries disappears definitely by construction. Concerning the estimate of the Africa-Dummy it is expected that the sorting out of especially poor countries - as it is them who have the weakest databases - will cause a positive bias, i.e. the punishment of being a Sub-Saharan countries might be underestimated. In contrast, the countries that are excluded for one of the other above mentioned reasons did not show any structural similarities so that it is unlikely that they cause a selection bias. The complete list of countries included in our sample is given in Table 1.

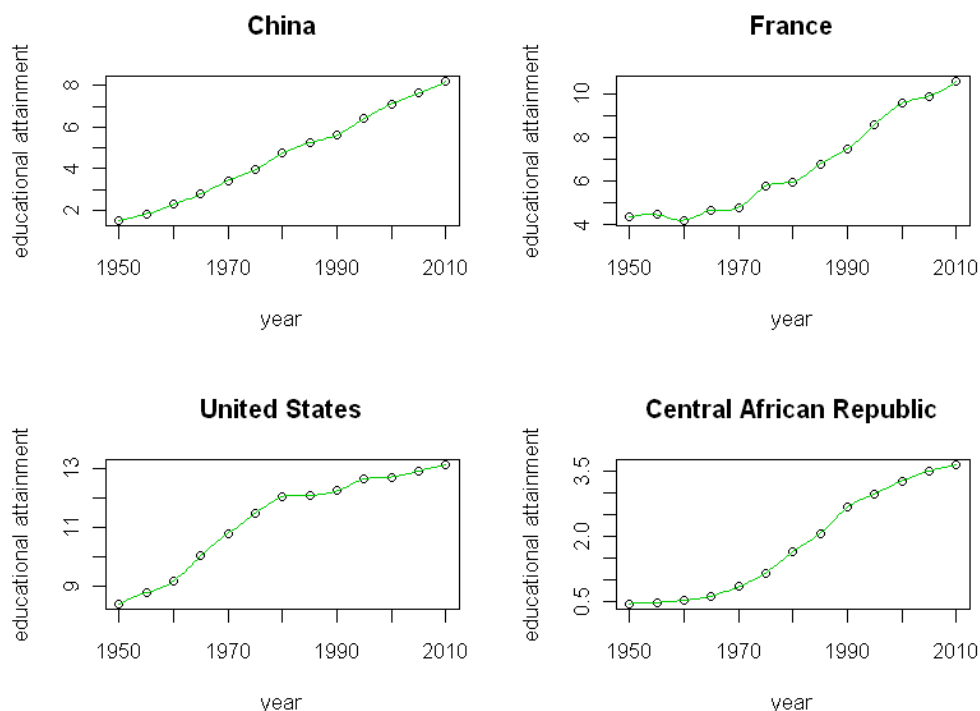


Figure 1: Interpolation of schooling.

Because economic growth is a consequence of changes in the production function, the output of the economy is measured as the real per worker gross domestic product (GDP). This answers the question how much each productive factor contributes on average to the growth in its country. We denote the logarithm of the per worker GDP of country i at time t by y_{it} .

Table 1: List of countries included in our sample

Code	Country	Code	Country	Code	Country
ARG	Argentina	AUS	Australia	AUT	Austria
BEL	Belgium	BEN	Benin	BGD	Bangladesh
BOL	Bolivia	BRA	Brazil	BRB	Barbados
BWA	Botswana	CAN	Canada	CHE	Switzerland
CHL	Chile	CHN	China	CMR	Cameroon
COG	Congo	COL	Colombia	CRI	Costa Rica
DNK	Denmark	DOM	Dominican Republic	ECU	Ecuador
EGY	Egypt	ESP	Spain	FIN	Finland
FJI	Fiji	FRA	France	GBR	United Kingdom
GHA	Ghana	GRC	Greece	GTM	Guatemala
HKG	Hong Kong	HND	Honduras	IDN	Indonesia
IND	India	IRL	Ireland	IRN	Iran
ISL	Iceland	ISR	Israel	ITA	Italy
JAM	Jamaica	JOR	Jordan	JPN	Japan
KEN	Kenya	KOR	Korea	LKA	Sri Lanka
MEX	Mexico	MLI	Mali	MUS	Mauritius
MWI	Malawi	MYS	Malaysia	NER	Niger
NGA	Nigeria	NLD	Netherlands	NOR	Norway
NPL	Nepal	NZL	New Zealand	PAK	Pakistan
PAN	Panama	PER	Peru	PHL	Philippines
PRT	Portugal	PRY	Paraguay	ROM	Romania
RWA	Rwanda	SEN	Senegal	SGP	Singapore
SLE	Sierra Leone	SLV	El Salvador	SWE	Sweden
SYR	Syria	THA	Thailand	TTO	Trinidad Tobago
TUN	Tunisia	TUR	Turkey	TZA	Tanzania
URY	Uruguay	USA	USA	VEN	Venezuela
ZAF	South Africa	ZMB	Zambia	ZWE	Zimbabwe

The population growth refers to the working age population which is defined in the PWT as all individuals from 15 to 64 years. The data for the total population are multiplied by the share of adults in working age. We denote the growth rate of the working age population of country i at time t by n_{it} . For depreciation rates there is some accordance in the literature, see also [Mankiw, Romer and Weil \(1992\)](#), to expect the capital to wear out by 3% per year and an advance in productivity of 2% per year for all countries. We denote the logarithm of its sum plus n_{it} simply by lnn_{it} . The saving rate of the economy is approximated by the relative investment share of the real GDP. We denote the logarithm of the share of country i at year t by $lnsk_{it}$. The proxy for human capital is the educational attainment data from [Barro and Lee \(2010\)](#) denoted by $lnattain_{it}$. As they were given in five years frequencies the missing values are extrapolated by interpolation splines, see the examples of China, France, US and Central African Republic in [Figure 1](#).

Most time-series have a short term cyclical component and a trend component. The Solow

model addresses long run growth but not the cyclical fluctuations. Therefore, it is recommendable to smooth the data. As the series have different magnitudes of short term fluctuations they have to be treated in different ways. However, the series lnn_{it} and $lnattain_{it}$ have only negligible short term fluctuations and are therefore not to be smoothed. The series $lnsk_{it}$ and y_{it} have severe cyclical components. We tried three possible procedures: regression smoothing, three and five years averaging, and applying the filter of [Hodrick and Prescott \(1997\)](#). Contrary to many other papers we finally decided for the last option for different reasons, see [Köhler \(2012\)](#) for details. The so-called HP filter decomposes a macroeconomic time-series $\tilde{\tau}_t$ in a structural trend component τ_t , which accounts for sustainable long-run growth and a cyclical component c_t , i.e.

$$\min_{\tau_t} \sum_{t=1}^T (\tilde{\tau}_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} ((\tau_{t+1} - \tau_t)(\tau_t - \tau_{t-1}))^2.$$

[Hodrick and Prescott \(1997\)](#) argue that $\lambda = 1600$ is a reasonable choice for quarterly data which intuitively corresponds to a value of 400 for yearly data. On the other hand, [Baxter and King \(1999\)](#) argue that λ should be chosen as the fourth power of a change in the frequency. In our case this corresponds to 6.25. After observing the different outputs of the smoothing with different smoothing parameters, we decided to chose the compromises $\lambda = 100$ for yearly growth, and $\lambda = 25$ for $lnsk$, whereas the other series were already that smooth that the HP filter for $100 \geq \lambda \geq 25$ did not really change the series. [Figure \(2\)](#) shows the smoothed series of the yearly growth rates and [Figure \(3\)](#) for $lnsk$ of the four countries Belgium, Kenya, Guatemala and Philippines.

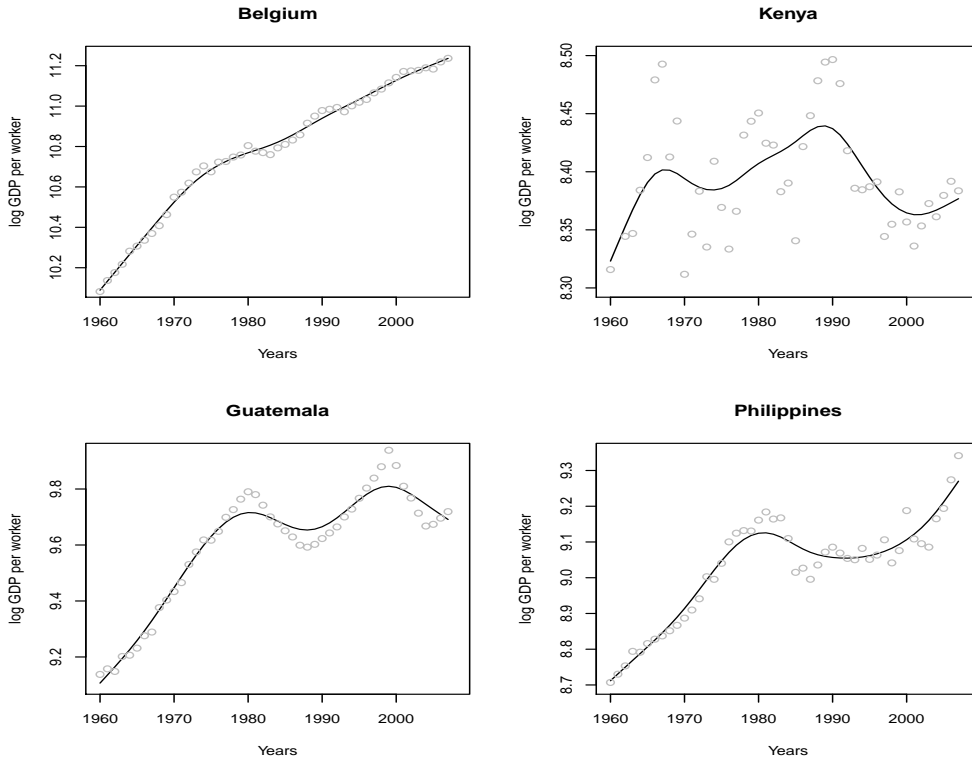


Figure 2: HP Smoothing of y_{it} with $\lambda = 100$.

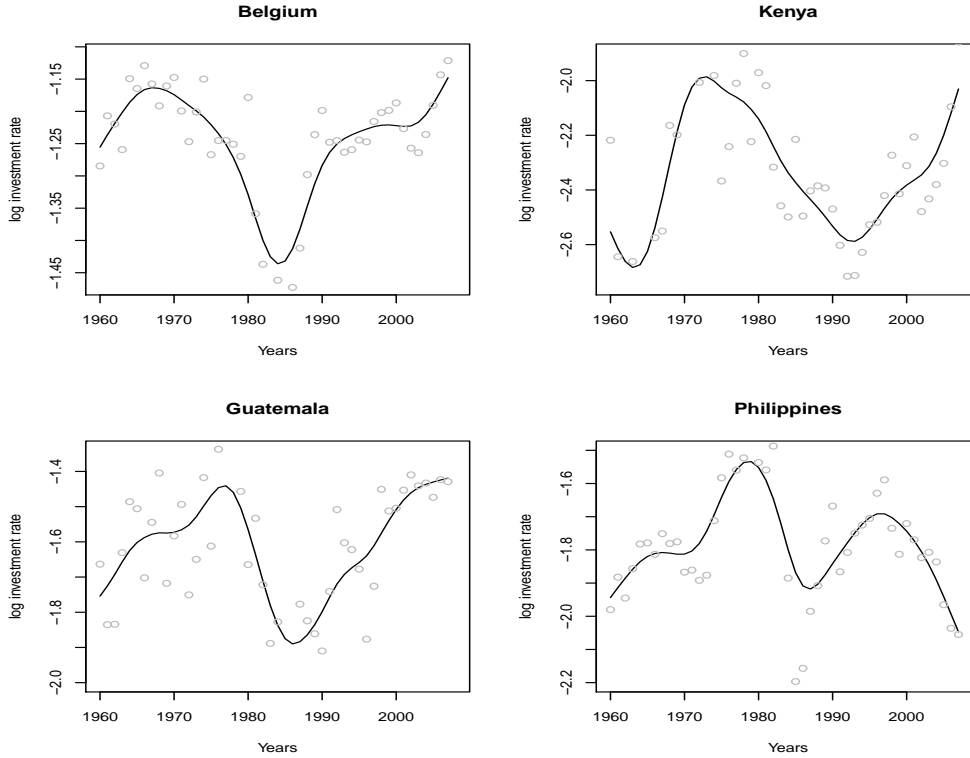


Figure 3: HP Smoothing of $lnsk_{it}$ with $\lambda = 25$.

The literature deriving the augmented Solow growth model is abundant, already for the context of panels. Starting from the neoclassical Solow model they basically all end up with

$$y_{it} = \rho * y_{i(t-1)} + \beta_1 * lnn_{it} + \beta_2 * lnsk_{it} + \beta_3 * lnattain_{it} + \eta_t + \eta_i + \nu_{it}, \quad (1)$$

where η_t are time fixed effects which might be skipped as argued by [Islam \(1995\)](#) - although he later on reincluded them to control for business cycles as he did no presmoothing - or be modeled linearly as $\eta_t = \beta_4 t$, see [Sperlich and Sperlich \(2012\)](#). As after the HP smoothing the time trend turned out to be insignificant, we skipped it following the arguments of [Islam \(1995\)](#). Further, η_i stands e.g. for technical and other fixed factor differences like climate, land-lockedness, etc., and ν_{it} for the remaining unexplained heterogeneity with expectation zero. Note however, that if the η_i are modeled as fixed effects without further constraints, they impede the identification of any effect coming from other time invariant factors. Where those were of interest, people typically estimate first a fixed effects model as (1) and in a second step regress the obtained $\hat{\eta}_i$ on the (fixed) factors of interest like e.g. the Africa-Dummy. Then, for further inference a correct calculation of standard errors and correlations between the estimates is necessary but typically lacking².

²Actually, the most common procedure in the literature is to simply believe the standard errors obtained in the second step ignoring the former step, what is just wrong.

3 Identifying the Africa-Dummy

We denote the information of the dependent variable from some initial time point 1 up to t by $y_i^t = (y_{i1}, \dots, y_{it})$ and the information of the exogenous variables from some initial time point 2 up to t by $x_i^t = (x'_{i2}, \dots, x'_{it})$. We assume that $\{(y_i^T, x_i^T), i = 1, \dots, n\}$ are independent observations from the same probability distribution, with finite first and second order moments. We are aiming for estimating (1) with the Africa-Dummy. If $\beta = (\beta_1, \beta_2, \beta_3, \beta_4)'$ and x the corresponding regressors, then (1) can be written as

$$y_{it} = \rho y_{i(t-1)} + x'_{it} \beta + \eta_i + \nu_{it}. \quad (2)$$

where the Africa-Dummy is a part of the country-specific effects

$$y_{it} = \eta_g + \rho y_{i(t-1)} + x'_{it} \beta + SSH * 1_{SSH,i} + \tilde{\eta}_i + \nu_{it} \quad (3)$$

with $E(\tilde{\eta}_i) = 0$, $1_{SSH,i}$ equals 1 if country i belongs to the group of sub-Saharan African countries and 0 else, and η_g is the common intercept. We assume

$$E(\nu_{it} | 1_{SSH,i}, y_i^{t-1}, x_i^T, \tilde{\eta}_i) = 0 \quad (4)$$

and

$$E(\nu_{it} \nu_{js}) = \begin{cases} \sigma_\nu^2, & \text{if } i = j \text{ and } s = t \\ 0, & \text{if } i \neq j \end{cases}. \quad (5)$$

We can relax these assumptions to allow the errors to be autocorrelated and heteroscedastic. This might be handled then by GLS estimation or robust standard errors. The country specific effects reflect the general productivity plus country specific characteristics like resources, climate, institutions, landlockedness, etc., recall discussion above.

For a vector-matrix notation we stack the time-series data, i.e.

$$y_i = (y_{i2}, \dots, y_{iT})' \in \mathbb{R}^{T-1}, \quad y_{i(-1)} = (y_{i1}, \dots, y_{i(T-1)})' \in \mathbb{R}^{T-1} \\ \iota = (1, \dots, 1)' \in \mathbb{R}^{T-1}, \quad X_i = (x_{i2}, \dots, x_{iT}) \in \mathbb{R}^{K \times (T-1)}, \quad \nu_i = (\nu_{i2}, \dots, \nu_{iT})' \in \mathbb{R}^{T-1}$$

and further

$$y = (y'_1, \dots, y'_n)' \in \mathbb{R}^{n(T-1)}, \quad y_{-1} = (y'_{1(-1)}, \dots, y'_{n(-1)})' \in \mathbb{R}^{n(T-1)} \\ X = (X_1, \dots, X_n)' \in \mathbb{R}^{n(T-1) \times K}, \quad C = I_n \otimes \iota \in \mathbb{R}^{n(T-1) \times n} \\ \eta = (\eta_1, \dots, \eta_n)' \in \mathbb{R}^n, \quad \nu = (\nu'_1, \dots, \nu'_n)' \in \mathbb{R}^{n(T-1)}. \quad .$$

Equation (2) can then be written as

$$y = \rho y_{-1} + X \beta + C \eta + \nu \in \mathbb{R}^{n(T-1)} \quad (6)$$

and (3) can be stacked in the same way. We assume without loss of generality that the data are available in the form that exactly the first s rows belong to the group of sub-Saharan African countries. Denote

$$\tilde{\eta} = (\tilde{\eta}_1, \dots, \tilde{\eta}_n)' \in \mathbb{R}^n, \quad \iota_{n(T-1)} = (1, \dots, 1)' \in \mathbb{R}^{n(T-1)} \quad \text{and} \\ \iota_{n(T-1), SSH} = \left(\underbrace{1, \dots, 1}_{\in \mathbb{R}^{s(T-1)}}, \underbrace{0, \dots, 0}_{\in \mathbb{R}^{(n-s)(T-1)}} \right) \in \mathbb{R}^{n(T-1)}. \quad .$$

Now, model (3) can be in stacked as

$$y = \iota_{n(T-1)}\eta_g + \rho y_{-1} + X\beta + \iota_{n(T-1),SSH} * SSH + C\tilde{\eta} + \nu \in \mathbb{R}^{n(T-1)}. \quad (7)$$

Regression equations (2) and (3) have a lagged dependent variable. Therefore, including the lagged dependent variable will cause a bias when estimating the coefficients, see [Nickell \(1981\)](#) for panels with fixed T . In consequence, several bias reduction procedures have been proposed, for example by [Kiviet \(1995\)](#), [Hahn and Kuersteiner \(2002\)](#) or [Phillips and Sul \(2007\)](#). We calculate the bias of Within Group estimator using the formulas provided in the article of [Phillips and Sul \(2007\)](#) for different ρ 's. The results show that the biases are negligible small being $\ll 0.001$ for the β estimates, and even $\ll 10^{-16}$ for the fixed effects and the Africa-Dummy.

Running the regressions using exactly (3) has three drawbacks. First, the one year growth time-series shows little variation so that the coefficient of the lagged dependent variable is close to one with all other coefficients being quite small. Second, since the economy can choose its growth driving parameters simultaneously to growth, it is more natural to assume that the drivers are the lagged values of our regressors. Third, most of the other authors considered five year time horizons taking either averaged or initial explanatory variables to represent the time horizons. So for the sake of comparison we prefer also to look at 5-year horizons. However, taking 5-years lagged variables has two drawbacks: we move away from the situation described by [Mankiw, Romer and Weil \(1992\)](#) and since the model deals with the evolution of the differences of the logarithms of the subsequent GDP's, 5-year horizons might generate differences that are too large to approximate growth by log-differences $\ln(GDP_t) - \ln(GDP_{t-1}) \approx (GDP_t - GDP_{t-1})/GDP_{t-1}$. Therefore we always run the regression with a one year lagged dependent variable and contemporary explanatory variables and recheck the results with a regression with a five year lagged dependent variable and five year lagged explanatory variables.

[Caselli, Esquivel, Lefort \(1996\)](#) applied the Difference GMM ([Arellano and Bond \(1995\)](#)) to growth regression using linear smoothed data with five year time horizons between 1960 and 1985, but [Bond, Hoeffler and Temple \(2001\)](#) noted that the Difference GMM uses weak instruments because the series of the logarithms of GDP's per capita is highly persistent and recommend the System GMM. Later on, many papers have appeared using the System GMM. [Hoeffler \(2002\)](#) addresses the problem of estimating the Africa-Dummy in growth regressions (using a two-step procedure as indicated above) coming to the conclusion that System GMM is the preferred method. As most authors use linear smoothing instead of applying the HP filter, their time-series are short which leads to few instruments. The number of instruments when having time-series data with $T = 48$ is however very large causing various problems. One general problem of GMM is a bias that occurs when too many instruments are used, see for example [Tauchen \(1986\)](#) or [Ziliak \(1997\)](#). Serious problems occur also when estimating the optimal weighting matrix of GMMs. The number of elements to be estimated is quadratic in the number of instruments and therefore quartic in T . Moreover, the elements of the optimal matrix are fourth moments of the underlying distributions because they are second moments of the result of differenced variables times variables. [Roodman \(2009\)](#) notes that a common symptom for estimations of the weighting matrix is that they are singular. Therefore, the generalized inverse rather than the inverse

is calculated. This can give results that are far away from the theoretical one on which further inference is built up. The breakdown tends to occur as the number of instruments approaches (from below) n . Note that we have 4554 instruments with only $n = 81$ countries when using the System GMM.

Different procedures were proposed to reduce the number of instruments. The Hansen J-Test (see Hansen (1982)) usually checks the validity of instruments, but as for example Bowsher (2002) observed, a too large number of instruments weakens the test dramatically, see also Roodman (2009). There does not exist a reliable test available that tells us how many and which instruments to choose. Finally, note that the System GMM shows serious biases when the variation of the fixed effects is larger than the residual's variance (what for macro models is almost always the case), see e.g. Hayakawa (2007), and that the required crucial initial conditions are least likely to be fulfilled in case of highly persistent time-series as in our case, see again Roodman (2009). All together, with the inefficiency and problems of correct inference of a two-step method to calculate the Africa-Dummy estimate, it is not surprising that using System GMM one obtains insignificant results.

To be able to identify and estimate (3) directly, we assume that the errors of the sub-Saharan African countries sum up to zero and that the errors of the non-sub-Saharan African countries sum up to zero separately

$$\sum_{i=1}^s \tilde{\eta}_i = 0 \text{ and } \sum_{i=s+1}^n \tilde{\eta}_i = 0. \quad (8)$$

With this assumption specify

$$y = \rho y_{-1} + X\beta + C_{SSH}\eta_{SSH} + \nu \in \mathbb{R}^{n(T-1)}, \quad (9)$$

$$\eta_{SSH} = (\eta_g, SSH, \tilde{\eta}_1, \dots, \tilde{\eta}_{s-1}, \tilde{\eta}_{s+1}, \dots, \tilde{\eta}_{n-1})' \in \mathbb{R}^n$$

$$C_{SSH} = \begin{pmatrix} \iota & \iota & \iota & & & \\ \vdots & \vdots & & \ddots & & \\ \iota & \iota & & & \iota & \\ \iota & \iota & -\iota & \cdots & -\iota & \\ \hline \iota & & & & \iota & \\ \vdots & & & & & \ddots \\ \iota & & & & & & \iota \\ \iota & & & & -\iota & \cdots & -\iota \end{pmatrix} \in \mathbb{R}^{n(T-1) \times n},$$

where the lower right box refers to the non-sub-Saharan African countries and has $n - s - 1$ columns and $(n - s)(T - 1)$ rows and the upper middle box refers to the sub-Saharan African

countries and has $s - 1$ columns and $s(T - 1)$ rows. It is easy to check that

$$C'_{SSH}C_{SSH} = (T - 1) \begin{pmatrix} Z_1 & & \\ & Z_2 & \\ & & Z_3 \end{pmatrix} \in \mathbb{R}^{n \times n}, \quad Z_1 = \begin{pmatrix} n & s \\ s & s \end{pmatrix},$$

$$Z_2 = \begin{pmatrix} 2 & 1 & \dots & 1 \\ 1 & 2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 1 \\ 1 & \dots & 1 & 2 \end{pmatrix} \in \mathbb{R}^{(s-1) \times (s-1)}, \quad Z_3 = \begin{pmatrix} 2 & 1 & \dots & 1 \\ 1 & 2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 1 \\ 1 & \dots & 1 & 2 \end{pmatrix} \in \mathbb{R}^{(n-s-1) \times (n-s-1)}.$$

The inverses of Z_1 , Z_2 and Z_3 exist and are given by

$$Z_1^{-1} = \frac{1}{n-s} \begin{pmatrix} 1 & -1 \\ -1 & n/s \end{pmatrix} \in \mathbb{R}^{2 \times 2},$$

$$Z_2^{-1} = \frac{1}{s} \begin{pmatrix} (s-1) & -1 & \dots & -1 \\ -1 & (s-1) & \ddots & \vdots \\ \vdots & \ddots & \ddots & -1 \\ -1 & \dots & -1 & (s-1) \end{pmatrix} \in \mathbb{R}^{(s-1) \times (s-1)},$$

and

$$Z_3^{-1} = \frac{1}{n-s} \begin{pmatrix} (n-s-1) & -1 & \dots & -1 \\ -1 & (n-s-1) & \ddots & \vdots \\ \vdots & \ddots & \ddots & -1 \\ -1 & \dots & -1 & (n-s-1) \end{pmatrix} \in \mathbb{R}^{(n-s-1) \times (n-s-1)}.$$

It follows that

$$(C'_{SSH}C_{SSH})^{-1} = \frac{1}{T-1} \begin{pmatrix} Z_1^{-1} & & \\ & Z_2^{-1} & \\ & & Z_3^{-1} \end{pmatrix} \in \mathbb{R}^{n \times n}.$$

Note that the existence of $(C'_{SSH}C_{SSH})^{-1}$ is equivalent to that the columns of C_{SSH} are linear independent, meaning that the model can be identified. It is now easy to check that

$$M_{C_{SSH}} = I_{n(T-1)} - C_{SSH}(C'_{SSH}C_{SSH})^{-1}C'_{SSH} = I_{n(T-1)} - I_n \otimes \mathbf{u}' \in \mathbb{R}^{n(T-1) \times n(T-1)}.$$

Therefore, ρ and β can be estimated by the Within Group estimator. Furthermore,

$$\hat{\eta}_{SSH} = (C'_{SSH}C_{SSH})^{-1}C'_{SSH}(y - \hat{\rho}_{WG}y_{-1} - X\hat{\beta}_{WG}).$$

Solving this gives the Two-Groups Least-Square Dummy-Variable estimator

$$\begin{aligned} \hat{\rho} &= \hat{\rho}_{WG}, \quad \hat{\beta} = \hat{\beta}_{WG}, \quad \hat{\eta}_g = \bar{\eta}_{NA}, \quad S\hat{S}H = \bar{\eta}_A - \bar{\eta}_{NA}, \\ \hat{\eta}_j &= \bar{\eta}_j - \bar{\eta}_A \text{ for } j \in \{1, \dots, s-1\} \text{ and } \hat{\eta}_j = \bar{\eta}_j - \bar{\eta}_{NA} \text{ for } j \in \{s+1, \dots, n-1\}. \end{aligned} \quad (10)$$

With (10) and $-\tilde{\eta}_1 - \dots - \tilde{\eta}_{s-1} = \tilde{\eta}_s$ we have $\hat{\eta}_s = \bar{\eta}_s - \bar{\eta}_A$ and in the same manner $\hat{\eta}_n = \bar{\eta}_n - \bar{\eta}_{NA}$. The total country-specific effect of a sub-Saharan African country with

index $j \in \{1, \dots, s\}$ is $\hat{\eta}_g + S\hat{S}H + \hat{\eta}_j = \bar{\eta}_j$ and that of a non-sub-Saharan African country with index $j \in \{s + 1, \dots, n\}$ is $\hat{\eta}_g + \hat{\eta}_j = \bar{\eta}_j$. The Two-Groups Least-Square Dummy-Variable estimator allows to reliably estimate the correlations of the Africa-Dummy to other regressors. Furthermore, as it does not use the inefficient Instrumental Variable method, it is more efficient. Another example of the Least-Squares method is that it remains being consistent even if the residuals are heteroscedastic and serially correlated.

4 Empirical Results for different Specifications

Table (2) show the estimated coefficients with its standard errors. The outcome and interpretation of the five year lagged model is similar to that of the one year lagged model for all estimation methods. The coefficient of *lnn* is almost zero in the one year lagged model and at least becomes negative significant on ten percent level in the five year lagged model. We will see later that this is due to the heterogeneity between the different regions. As often observed, the coefficient of *lnattain* is negative. Note that the indicator by [Barro and Lee \(2010\)](#) does not take the quality of schooling into account. Further, even when their data were corrected for the account change after 2005 (in some countries) the school attainment increases for almost all countries while the growth rate does not. The numerical consequence is a negative coefficient³.

Table 2: Two Groups Fixed Effects Estimates with standard errors

	one year lag		five years lag	
Intercept	0.1795***	(0.0117)	1.1343***	(0.0635)
lag y	0.9897***	(0.0011)	0.8926***	(0.0061)
lnn	0.0008	(0.0025)	-0.0240	(0.0127)
lnsk	0.0275***	(0.0012)	0.0813***	(0.0063)
lnattain	-0.0150***	(0.0010)	-0.0493***	(0.0053)
SSH	-0.0109***	(0.0017)	-0.1551***	(0.0090)

* $p : \leq 0.05$ ** ≤ 0.01 *** ≤ 0.001

When next looking at the correlation of the coefficients we see that the Africa-Dummy is larger, the smaller the coefficient of *lnn* or *lnattain* are or the larger the coefficient of *lnsk* is. Nevertheless, its correlations to the coefficient of *lnattain* and *lnn* are small. In other words, if the return to investment in physical capital increases, the punishment of belonging to sub-Saharan Africa decreases. Furthermore, if the return to the depreciation rate or the school attainment increases, the punishment of belonging to Sub-Saharan Africa increases.

Table 3: Correlation of Africa-Dummy with other coefficient estimates

Model	Corr lnn	Corr lnsk	Corr lnattain
one year lag	-0.1170	0.5641	-0.0938
five years lag	-0.1279	0.5252	-0.0537

³Recall that we are estimating only the impact of country specific (i.e. within) variation.

The Two-Groups Least-Square Dummy-Variable estimator is able to estimate the decomposition $\tilde{\eta}_i + \eta_g + SSH * 1_{SSH;i}$. We denote $\tilde{\eta}_i + \eta_g + SSH * 1_{SSH;i}$ by fixed effects and $\tilde{\eta}_i + \eta_g$ by corrected fixed effects. The corrected fixed effects are larger than the fixed effects in case of a sub-Saharan African country and equal for all other countries. Figure (4) shows boxplots of the fixed effects in the five years lagged model. We observe that both distributions are slightly skewed to the left. The tails of the corrected fixed effect support a symmetric distribution but as the median is closer to the first quartile than to the third quartile, the distribution is also slightly skewed to the left.

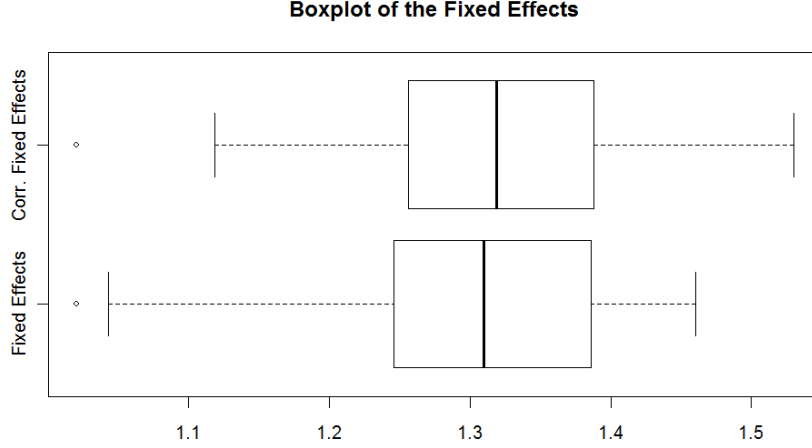


Figure 4: Boxplot of the fixed effects for the five year lagged model.

Let us turn to the semiparametric modeling to account for possible functional misspecification. The growth model by [Mankiw, Romer and Weil \(1992\)](#) suggests the regression equation (3) which has a linear functional structure. We investigate if a misspecification of this functional structure is responsible for that the Africa-Dummy is negative and significant. Note that functional misspecification causes biased coefficient estimates similar to those of the biases of omitted variable, see [Köhler \(2012\)](#) for more details. We use cubic B-Splines of degree three with equidistant knots to relax the functional structure of the variables lnn , $lnsk$ and $lnattain$. The number of knots has been chosen in a way that takes the sample size as well as the number of regressors into account. Akaike's Information Criterion results in choosing models with too many parameters when having large samples. The Bayesian Information Criterion punishes harder for choosing a lot of explanatory variables. Therefore, we chose the number of knots with respect to that it minimizes the Bayesian Information Criterion. More precisely, we vary the number of knots between three and ten and choose the combination that minimizes the Bayesian Information Criterion. The result for the one year lagged model is zero knots for the variables lnn , $lnattain$, and one knot for the variable $lnsk$. The result for the five year lagged model is one knot for all variables. When running these regressions we observe that the coefficient of the lagged dependent variable increases from 0.9897 to 0.9920 in the one year lagged model and decreases from 0.8926 to 0.8911 in the five year lagged model. The intercept decreases from 0.1905 to 0.0322 in the one year lagged model and from 1.2894 to 0.8834 in the five year lagged model. The magnitude of the Africa-Dummy increases slightly from -0.0109 to -0.0113 in the one year

lagged model and from -0.1551 to -0.1582 in the five year lagged model. In both cases we observe a highly significant Africa-Dummy, i.e. the significance of the Africa-Dummy cannot be explained by a misspecification of the functional structure in an additive model.

We next turn to the question of potential interaction effects and consider model (3) with interactions effects that allow for time varying punishments of sub-Saharan African countries, i.e. we add $x_{it}1_{SSH,i}$ to equation (3). The results are given in Table (4). There we observe a positive significant interaction effect of the coefficient of lnn , where now, cf. Table (4), the return to lnn is significant negative as predicted by economic growth theory. For the one year lagged model the total coefficient of lnn is $-0.0129 + 0.0357 = 0.0228$ and for the five year lagged model $-0.0760 + 0.1535 = 0.0775$, i.e. in Africa population growth has a positive impact on growth what is probably not that surprising given the dominance of the manufacturing and (mainly man power based) agricultural sectors. The negative interaction with the base GDP (in the five years lag model) indicates that African countries converge faster when controlling for the interaction with lnn . Further interactions are insignificant except with $lnattain$ in the one-year lag model at the 5% level. Surprisingly, having controlled for the specific African feature of positive impact of population growth on GDP, the Africa-Dummy is significantly positive. All in all, accounting for the special (higher) returns to population growth in Africa we find faster beta-convergence and higher conditional growth for Sub-Saharan African countries.

Table 4: Estimates and standard errors of the growth regression with interactions

	one year lag		five years lag	
Intercept	0.1588***	(0.0134)	1.0938***	(0.0724)
SSH	0.0646*	(0.0266)	0.6151***	(0.1451)
lag y	0.9895***	(0.0013)	0.8976***	(0.0070)
1_{SSH} lag y	0.0020	(0.0027)	-0.0397**	(0.0147)
lnn	-0.0129***	(0.0031)	-0.0760***	(0.0159)
1_{SSH} lnn	0.0357***	(0.0052)	0.1535***	(0.0265)
$lnsk$	0.0268***	(0.0016)	0.0752***	(0.0081)
1_{SSH} $lnsk$	0.0028	(0.0025)	0.0145	(0.0129)
$lnattain$	-0.0175***	(0.0013)	-0.0498***	(0.0070)
1_{SSH} $lnattain$	0.0047*	(0.0020)	0.0017	(0.0108)

* $p : \leq 0.05$ ** ≤ 0.01 *** ≤ 0.001

To investigate how the Africa-Dummy evolves over time consider model

$$y_{it} = \eta_g + \rho y_{i(t-1)} + x'_{it}\beta + \sum_{s=2}^T SSH_s * d_{SSH,t}(i, s) + \tilde{\eta}_i + \nu_{it}, \quad (11)$$

with $t = 2, \dots, T$ and $i = 1, \dots, n$, where $d_{SSH,t}(i, s) = 1$ if country i belongs to sub-Saharan Africa and $s = t$ and $d_{SSH,t}(i, s) = 0$ else, and still $\sum_{i=1}^s \tilde{\eta}_i = 0$, $\sum_{i=s+1}^n \tilde{\eta}_i = 0$ for identifying the model. Stacking first time-series and then cross-sectional data yields

$$y = \rho y_{-1} + X\beta + (\iota_{SSH} \otimes I_{T-1})SSH + C\eta + \nu \in \mathbb{R}^{n(T-1)},$$

where $SSH = (SSH_2, \dots, SSH_T)' \in \mathbb{R}^{T-1}$, $\eta = (\eta_g, \tilde{\eta}_1, \dots, \tilde{\eta}_{s-1}, \tilde{\eta}_{s+1}, \dots, \tilde{\eta}_{n-1})' \in \mathbb{R}^{n-1}$,

$$C = \left(\begin{array}{ccc|ccc} \iota & & & & & \\ \vdots & & & & & \\ \iota & & & & \iota & \\ \iota & -\iota & \cdots & -\iota & & \\ \hline \iota & & & & \iota & \\ \vdots & & & & & \ddots \\ \iota & & & & & \iota \\ \iota & & & & -\iota & \cdots & -\iota \end{array} \right) \in \mathbb{R}^{n(T-1) \times (n-1)}.$$

Note that this matrix does not contain the time varying Africa-Dummies. The lower right box refers to the non sub-Saharan African countries and has $n - s - 1$ columns and $(n - s)(T - 1)$ rows, the upper middle box refers to the sub-Saharan African countries and has $s - 1$ columns and $s(T - 1)$ rows and the first column refers to the intercept. The complete dummy matrix with the Africa-Dummies is $(\iota_{SSH} \otimes I_{T-1}, C) \in \mathbb{R}^{n(T-1) \times (n+(T-1))}$ and has full column rank. In the same way we formulate the five years lag model

$$y_{it} = \eta_g + \rho y_{i(t-5)} + x'_{i(t-5)} \beta + \sum_{s=6}^T SSH_s * d_{SSH,t}(i, s) + \tilde{\eta}_i + \nu_{it}.$$

Table 5: Coefficient estimates and standard errors for a model with time-varying Africa-Dummy

	one year lag		five years lag	
Intercept	0.1832***	(0.0117)	1.2654***	(0.0636)
lag y	0.9911***	(0.0011)	0.8964***	(0.0062)
Inn	0.0012	(0.0025)	-0.0214	(0.0128)
Insk	0.0277***	(0.0013)	0.0834***	(0.0065)
Inattain	-0.0175***	(0.0012)	-0.0510***	(0.0065)

* $p : \leq 0.05$ ** ≤ 0.01 *** ≤ 0.001

The results for the estimators of the coefficients are given in Table (5). We observe that the estimators of the coefficients of (11) are similar to the model with a static Africa-Dummy, equation (3). Figures (5) and (6) show that the Africa-Dummy varies a lot over time. Apart from the downward bumps during the oil crises in the mid 70s and the end of the cold war [together with the break down of the Eastern block economies] it had a general though small downward trend but then started to strongly increase since the mid-nineties. When considering the one year lagged model it even becomes insignificant about the turn of the Millennium. However, looking at the five years growth the Africa-Dummy is still significant though the punishment has decreased from about -0.20 to -0.08 . This is in accordance with our findings from the exercise with interaction terms. There we found a positive impact on conditional growth and that Sub-Saharan African countries have been converging somewhat faster in the last 50 years compared to the rest of the world.

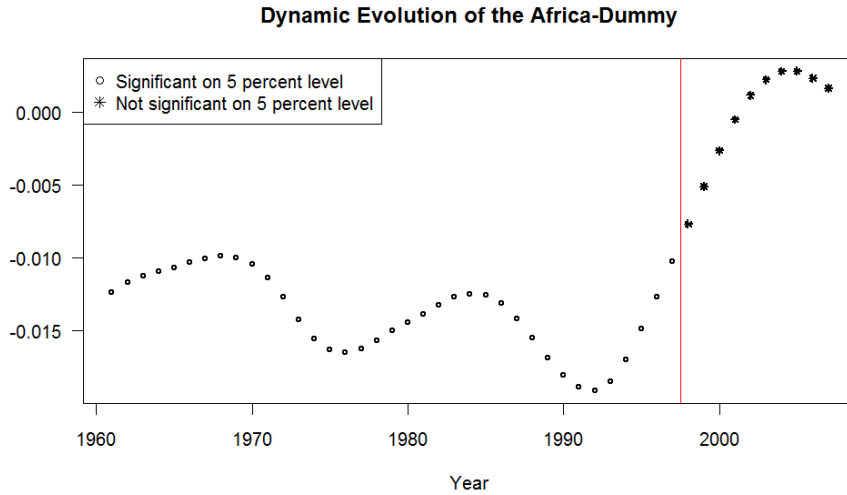


Figure 5: The Evolution of the Africa-Dummy in the one year lagged model

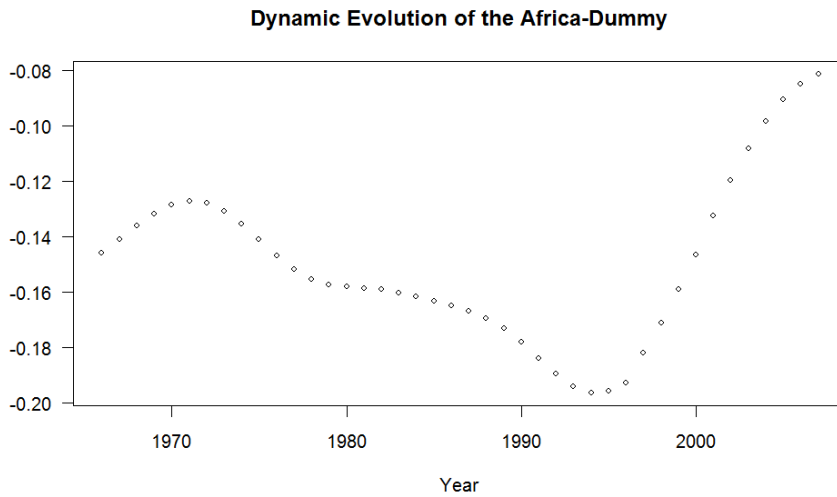


Figure 6: The Evolution of the Africa-Dummy in the five year lagged model

5 Conclusion

By smoothing the data with the Hodrick-Prescott filter we obtain yearly time-series that represent the connection of one time-series of an economy to another. When doing this, the length of the time-series is sufficiently large, so that the Nickel bias that may appear in a dynamic panel growth regression is negligibly small. The centering of the country specific fixed effects allows to identify and estimate the Africa Dummy directly in the classical growth model. This entails several advantages over the else so far used methods. Then, estimating the coefficients of the growth regression with the Two-Groups Least-Square Dummy-Variable estimator identifies a negative significant Africa-Dummy. The analysis of correlations of coefficient estimates reveals that this handicap for Sub-Saharan African economies increases if the return to investment in physical capital decreases, if the return to depreciation rate increases, or if the return to school attainment increases.

The Two-Groups Least-Square Dummy-Variable estimator is also used to relax the functional structure of the growth regression equation. We observe that the significance of the Africa-Dummy does not disappear when applying a semiparametric model so that it cannot be explained by a misspecification of the functional form. In contrast, when modeling the returns more flexibly we observe that Sub-Saharan African countries have clearly positive returns to the population growth rate, exhibit faster beta-convergence, such that the pure Africa-Dummy becomes even positive. As discussed, all these findings make sense but were hidden in former studies due to improper modeling and estimation methods. The imposing of equal returns for all regions in a world sample forces the Africa-Dummy to correct the mean, resulting in a negative coefficient.

Having seen that allowing for heterogeneous returns exhibits faster conditional growth and convergence for Sub-Saharan Africa, it is not surprising that when we estimate the evolution of the Africa-Dummy by our extended version of the Two-Groups Least-Square Dummy-Variable estimator, one can see how this gap diminishes. It can clearly be observed how the Africa-Dummy changes over time being strongly increasing since the mid-nineties. In the one year lag model it has even become insignificant in the recent years.

References

- ARELLANO, M. AND BOVER, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics* **69** 29–51.
- BAROSSA-FILHO, M. AND GONCALVES SILVA, R. AND MARTINS DINIZ, E. (2005). The Empirics of the Solow Growth Model: Long-Term Evidence. *Journal of Applied Economics* **8**(1) 31–51.
- BARRO, R. J. AND LEE, J. W. (2010). A New Data Set of Educational Attainment in the World, 1950–2010. National Bureau of Economic Research, Working Paper 15902.
- BARRO, R. J. AND MANKIW, N. G. AND SALA-I-MARTIN, X. (1995). Capital Mobility in Neoclassical Models of Growth. *American Economic Review* **85**(1) 103–115.
- BAXTER, M. AND KING, R. G. (1999). Measuring Business Cycles: Approximate Band-Pass Filters for Economic time-series. *The Review of Economics and Statistics* **81**(4) 575–593.
- BOND, S. AND HOEFFLER, A. AND TEMPLE, J. (2001). GMM Estimation of Empirical Growth Models. CEPR Discussion Paper 3048
- BOWSER, C. G. (2002). On testing overidentifying restrictions in dynamic panel data models. *Economics Letters* **77** 211–220.
- CASELLI, F. AND ESQUIVEL, G. AND LEFORT, F. (1996). Reopening the Convergence Debate: A New Look at Cross-Country Growth Empirics. *Journal of Economic Growth* **1**(3) 363–389.

- COLLIER, P. AND GUNNING, J. W. (1999). Explaining African Economic Performance. *Journal of Economic Literature* **37**(1) 64–111.
- EASTERLY, W. AND LEVINE, R. (1997). Africa’s Growth Tragedy: Policies and Ethnic Divisions. *The Quarterly Journal of Economics* **112**(4) 1203–50.
- GEORGESCU-ROEGEN, N. (1975). Dynamic Models and Economic Growth. *World Development* **11-12**(3) 765–783.
- HAHN, J. AND KUERSTEINER, G. (2002). Asymptotically Unbiased Inference for a Dynamic Panel Model with Fixed Effects When Both n and T Are Large. *Econometrica* **70**(4) 1639–1657.
- HANSEN, L. P. (1982). Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica* **50**(4) 1029–1054.
- HAYAKAWA, K. (2007). Small sample bias properties of the system GMM estimator in dynamic panel data models. *Economics letters* **95** 32–38.
- HESTON, A. AND SUMMERS, R. AND ATEN, B. (2009). Penn World Table Version 6.3. *Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania*.
- HODRICK, R. J. AND PRESCOTT, E. C. (1997). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking* **29**(1) 1–16.
- HOEFFLER, A.E. (2002). The augmented Solow model and the African growth debate. *Oxford Bulletin of Economics and Statistics* **64**(2) 135–58.
- ISLAM, N. (1995). Growth Empirics: A Panel Data Approach. *The Quarterly Journal of Economics* **110**(4) 1127–70.
- KIVIET, J. (1995). On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. *Journal of Econometrics* **68** 53–78.
- KÖHLER, M. (2012). Econometric Studies on Flexible Modeling of Developing Countries in Growth Analysis. Dissertation at the University of Göttingen.
- LEVINE, R. AND RENELT, D. (1992). A Sensitivity Analysis of Cross-Country Growth Regressions. *The American Economic Review* **82**(4) 942–63.
- MANKIW, N.G. AND ROMER, D. AND WEIL, D.N. (1992). A Contribution to the Empirics of Economic Growth. *The Quarterly Journal of Economics* **107**(2) 407–37.
- NICKELL, S. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica* **49**(6) 1417–26.
- PHILLIPS, P. C. B. AND SUL, D. (2007). Bias in dynamic panel estimation with fixed effects, incidental trends and cross section dependence. *Journal of Econometrics* **137** 162–188.

- PRICE, G. N. (2003). Economic Growth in a Cross-section of Nonindustrial Countries: Does Colonial Heritage Matter for Africa? *Review of Development Economics* **7**(3) 478–495.
- ROODMAN, D. (2009). A Note on the Theme of Too Many Instruments. *Oxford Bulletin of Economics and Statistics* **71**(1) 135–158.
- SACHS, J. D. AND WARNER, A. M. (1997). Sources of Slow Growth in African Economies. *Journal of African Economies* **6**(3) 335–76.
- SPERLICH, S. AND SPERLICH, Y. (2012). Growth and Convergence in South-South Integration Areas: Empirical Evidence. Working paper at the University of Geneva.
- TAUCHEN, G. (1986). Statistical Properties of Generalized Method-of-Moments Estimators of Structural Parameters Obtained from Financial Market Data. *Journal of Business and Economic Statistics* **4**(4) 397–416.
- WERE, M. AND NAFULA, N. N. (2003). An Assessment of the Impact of HIV/AIDS on Economic Growth: The Case of Kenya. CESifo Working Paper Series 1034.
- ZILIAK, J. P. (1997). Efficient Estimation with Panel Data when Instruments Are Predetermined: An Empirical Comparison of Moment-Condition Estimators. *Journal of Business and Economic Statistics* **15**(4) 419–431.