Applied Economics Letters, 1994, **1**, 194–199

Another look at the evidence on foreign aid led economic growth

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Received 19 July 1994

We apply recent time series techniques to Mbaku' s Cameroon data to investigate the effects of foreign aid on economic growth. In contrast to Mbaku, we find some evidence to support the foreign aid led growth hypotheses in Cameroon. Our results illustrate the importance of testing hypotheses in an appropriate time series framework and the difficulties of time–series modelling with an insufficient span of data.

I. INTRODUCTION

Recently, several authors have considered whether foreign aid can lead to economic growth (e.g. Islam, 1992; Mbaku, 1993, 1994; Bring, 1994). Their models, derived from the neoclassical production function, are of the form:

$$GDPG_t = \beta_0 + \beta_1 SY_t + \beta_2 GRNTDY_t + \beta_3 LOANDY_t + \beta_4 POPG_t + \varepsilon_t \quad (1)$$

where:

GDPG = growth rate of real gross domestic product (GDP)
SY = savings–GDP ratio (proxy for domestic sourced investment)
GRNTDY = foreign aid grants (% of GDP)
LOANDY = foreign aid loans (% of GDP)
POPG = population growth rate (proxy for labour growth).

Mbaku (1993) estimates Equation 1, using OLS, with annual Cameroon data over 1971–90. He finds positive autocorrelation and so uses the Cochrane–Orcutt procedure. On the basis of 'significance' he concludes that foreign aid has an insignificant impact on growth. Islam (1992) undertakes a similar investigation for Bangladesh, though he also considers models which use lagged variables. He finds some support for a positive impact of foreign aid on economic growth.

Bring (1994) criticizes studies such as these. He questions whether the effects of foreign aid may take many years to affect growth; the impact of other variables on growth; the inadequacy of the causal model; the use of 'significance' tests; and the multicollinearity adjustments. In his reply, Mbaku (1994) supports his 1993 study and suggests that the 'important contribution [of Bring, 1994] is the fact that there is a need to develop better and more efficient models to use in the study of the effects of foreign resource flows on economic growth in developing countries' (p. 57).

The aim of this paper is to preliminarily address this last point. We illustrate how to use recent developments in the analysis of economic time series to test the foreign aid led growth hypothesis. We use Mbaku' s (1993) data for Cameroon. In particular, we distinguish between statistical *association* and statistical *causality*; we illustrate the importance of unit root and cointegration testing; and we consider how the model' s formulation impacts on the properties of *causality* tests. In Section II we briefly discuss one technique often used to formally test for *causality*. Section III applies this approach to Mbaku' s 1993 data, and the final section provides some conclusions.

II. METHODOLOGY

One statistical procedure to test for causality between foreign aid and economic growth is that proposed by Granger (1969) and popularized by Sims (1972): X 'Granger-causes' Y if X's history helps predict Y's current value, *ceteris paribus*. The premise is that if the event X causes the event Y then the event X should precede the event Y. Several Granger-causality tests have been proposed and studies have considered their applicability; see, e.g. Hamilton (1994, Chapter 11).

To test 'Granger-causality' we estimate a pth order vector autoregressive model (VAR(p)):

$$y_t = \Gamma_0 + \sum_{i=1}^{p} \Gamma_i y_{t-i} + u_t \quad t = 1,2, \ldots ,T \tag{2}$$

where y_t is:

$$y_t = (GDPG_t, SY_t, GRNTDY_t, LOANDY_t, POPG_t)',$$

Γ_0 contains intercept terms, Γ_i (i=1 to p) is a coefficient matrix and we assume u_t is iid $N(0,\Omega)$. Our particular interest is in the first equation of (2):

$$GDPG_t = \gamma_0 + \sum_{i=1}^{p} \gamma_{1i} GDPG_{t-i} + \sum_{i=1}^{p} \gamma_{2i} SY_{t-i} + \sum_{i=1}^{p} \gamma_{3i} GRNTDY_{t-i} + \sum_{i=1}^{p} \gamma_{4i} LOANDY_{t-i} + \sum_{i=1}^{p} \gamma_{5i} POPG_{t-i} + u_{1t} \tag{3}$$

where the γ coefficients are appropriate elements of $\Gamma_0, \Gamma_1, \ldots, \Gamma_P$. Then, we test, for instance, that *GRNTDY* does not 'Granger-cause' *GDPG* by H_0: $\gamma_{31} = \gamma_{32} = \ldots = \gamma_{3p} = 0$ *vs.* H_A: at least one $\gamma_{3j} \neq 0$, j=1,…,p using, say, a Wald test statistic, $W \xrightarrow{d} \chi^2_p$ under the null.[1] The validity of this distributional assumption depends on the time series properties of the data. For example, it is appropriate if each series is stationary. However, stationarity is atypical for economic time series.

Then, if each series is non-stationary and, say, integrated of order one ($I(1)$), the asymptotic χ^2_p distribution holds only if there is cointegration between the variables in y_t and (at least one of) the cointegrating vector(s) involves the variable considered under H_0 – here *GRNTDY* (Sims *et al.*, 1990; Toda and Phillips, 1993, 1994 (hereafter TP)).[2] TP term this 'sufficient' cointegration. They show that when there is no cointegration, W's limiting distribution: (i) for a non-intercept model or a constant/time trend model, is nonstandard but free of nuisance parameters; (ii) for a constant/no time trend model, will involve nuisance parameters. If 'insufficient' cointegration exists then W's asymptotic distribution is non-standard and may depend on nuisance parameters. These results assume knowledge of the number of cointegrating relationships (r): they need not hold if we estimate r.

An alternative framework for $I(1)$ series is the error correction model (ECM) (e.g. Engle and Granger, 1987; Johansen, 1988). We write Equation 2 in its ECM form:

$$\Delta y_t + \Gamma^*_0 + \sum_{i=1}^{p^*} \Gamma^*_i \Delta y_{t-i} + \Theta A' y_{t-1} + u_t \tag{4}$$

where $p^* = p-1$, Θ and A are $(5 \times r)$ full column rank matrices, $0 \leq r \leq 4$, and for $r>0$, $A' y_{t-1}$ is $I(0)$.

The ECM of (3) is:

$$\begin{aligned}\Delta GDPG_t &= \gamma^*_0 + \sum_{i=1}^{p^*} \gamma^*_{1i} \Delta GDPG_{t-i} + \sum_{i=1}^{p^*} \gamma^*_{2i} \Delta SY_{t-i} \\ &+ \sum_{i=1}^{p^*} \gamma^*_{3i} \Delta GRNTDY_{t-i} + \sum_{i=1}^{p^*} \gamma^*_{4i} \Delta LOANDY_{t-i} \\ &+ \sum_{i=1}^{p^*} \gamma^*_{5i} \Delta POPG_{t-i} + \theta_1 A' y_{t-1} + u_{1t} = \gamma^*_0 + \sum_{i=1}^{p^*} \gamma^*_{1i} \Delta GDPG_{t-i} \\ &+ \sum_{i=1}^{p^*} \gamma^*_{2i} \Delta SY_{t-i} + \sum_{i=1}^{p^*} \gamma^*_{3i} \Delta GRNTDY_{t-i} + \sum_{i=1}^{p^*} \gamma^*_{4i} \Delta LOANDY_{t-i} \\ &+ \sum_{i=1}^{p^*} \gamma^*_{5i} \Delta POPG_{t-i} + \theta_1 (\alpha_1' GDPG_{t-1} + \alpha_2' SY_{t-1} \\ &+ \alpha_3' GRNTDY_{t-1} + \alpha_4' LOANDY_{t-1} + \alpha_5' POPG_{t-1}) + u_{1t}\end{aligned}$$

where α_i is the i'th row of A and θ_1 is the first row of Θ. The hypothesis that *GRNTDY* does not 'Granger-cause' *GDPG* is then H^*_0: $\gamma^*_{31} = \gamma^*_{32} = \ldots = \gamma^*_{3p^*} = 0$ and $\theta_1 \alpha_3' = 0$. For non-cointegrated variables we test H^*_0: $\gamma^*_{31} = \gamma^*_{32} = \ldots = \gamma^*_{3p^*} = 0$ and the Wald test statistic, $W_{H^*_0} \xrightarrow{d} \chi^2_{p^*}$. For non-zero r, TP show, for the problem investigated here, that if $rank(\theta_1) = 1$ or $rank(\alpha_3) = 1$ then $W_{H0^*} \xrightarrow{d} \chi^2_p$ (irrespective of whether there is or is not a constant and/or time trend term).

Let $\hat{r}$ be an estimate of r and assume $I(1)$ variables, then TP suggest the following practical testing strategy:

1. If $\hat{r} = 0$, estimate a VAR in differences with no error correction term and test H^+_0
2. If $\hat{r} = 4$, regard the data as stationary and test for causality based on a levels VAR.
3. If $0 < \hat{r} < 4$, test $H^{\$}_0$: $\theta_1 = 0$; if $H^{\$}_0$ is rejected then test H^*_0, otherwise test H^+_0. Note that $W_{H^{\$}_0} \xrightarrow{d} \chi^2_r$

They recommend using a 5% nominal size for each sub-test, as their Monte Carlo experiment suggests this will typically give an overall test size of approximately 5% (asymptotically). We use their approach to determine whether Granger-causality exists between foreign aid and economic growth in Cameroon.

1 This is equivalent to the usual F-test. The F-test statistic, however, is not F distributed under H_0 because of the lags of the dependent variable among the regressors.

2 For a discussion of these time series properties, see, e.g. Hamilton (1994) and Banerjee *et al.* (1993).

3 We note the misspecification problems that this may introduce.

Table 1. Dickey-Fuller tests for the order of integration

VARIABLE/MODEL	H_0: $I(2)$ vs. H_A: $I(1)$		H_0: $I(1)$ vs. H_A: $I(0)$	
	t-statistic	Outcome	*t*-statistic	Outcome
GDPG				
Trend/constant	–4.468	reject H_0	–2.351	accept H_0
No trend/constant	–4.546	reject H_0	–1.744	accept H_0
No trend/no constant	–4.673	reject H_0	–1.516	accept H_0
SY				
Trend/constant	–3.110	accept H_0	–1.366	accept H_0
No trend/constant	–3.149	reject H_0	–1.583	accept H_0
No trend/no constant	–3.265	reject H_0	–0.440	accept H_0
GRNTDY				
Trend/constant	–4.724	reject H_0	–1.466	accept H_0
No trend/constant	–4.337	reject H_0	0.090	accept H_0
No trend/no constant	–4.534	reject H_0	0.785	accept H_0
LOANDY				
Trend/constant	–6.973	reject H_0	–2.301	accept H_0
No trend/constant	–6.375	reject H_0	–1.448	accept H_0
No trend/no constant	–6.678	reject H_0	–1.053	accept H_0

Notes: The integrating regression is: $\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{q} \delta_i \; \Delta y_{t-i} + \varepsilon_t$, where Q is chosen to ensure white noise.

We determined q by examining the autocorrelation and partial autocorrelation functions of the residuals from this regression (e.g. Giles *et al*., 1992): q=0 was appropriate in each case. The ADF test is of H_0:$\gamma = 0$ *versus* H_A:$\gamma<0$ using the *t*-statistic. The 5% *t*-critical values are –3.712, –3.052, –1.963 for the trend/constant, no trend/constant, no trend/no constant models respectively (MacKinnon, 1991, p. 275).

III. EMPIRICAL RESULTS: UNIT ROOTS, COINTEGRATION AND CAUSALITY

We need to determine:

1. the order of integration of each time series;
2. whether any cointegration exists;
3. the order of the VAR model.

We briefly examine each of these issues here, followed by the causality testing. We used SHAZAM(1993).

Tests abound for identifying the order of integration of a time series. Here we use the augmented Dickey–Fuller (ADF) test (e.g. Said and Dickey, 1984). *POPG* has several structural breaks, which affect the properties of the unit root test and the question of the stationarity of a time series (e.g. Perron, 1989) and, given the data restrictions, we could not satisfactorily identify *POPG's* order of integration. Consequently, we omitted *POPG* from the analysis.[3] Our results, given in Table 1, suggest that *GDPG, SY, GRNTDY* and *LOANDY* are each $I(1)$.

We now determine whether the four variables are cointegrated. One common technique is that proposed by Johansen (1988, 1991). This involves estimating the VAR system by full information maximum likelihood (FIML) and using likelihood ratio tests to estimate r. Unfortunately, Mbaku's data contains only 20 observations; we cannot even estimate an unrestricted VAR(1) model by FIML and a single equation method is required. One method is the OLS APPROACH.[4] We estimate the 'cointegrating regression' (CR):

$$GDPG_t = \zeta_0 + \zeta_1 SY_t + \zeta_2 GRNTDY_t + \zeta_3 LOANDY_t + z_t \quad (6)$$

which may include a trend term (Hansen, 1992). The cointegrating vector is $(1,-\zeta_1,-\zeta_2,-\zeta_3)$. We arbitrarily normalize on the first element of this vector; we could normalize on the other elements of y. Asymptotically, this normalization does not matter but it may in finite samples. Accordingly, we apply the cointegration test to the four possible CRs.

If cointegration exists then z_t is $I(0)$. So we apply a unit root test to the OLS residuals from the CR. We use the ADF procedure (see Table 2), and we find no evidence of cointegration. Then, following the TP strategy we model a first difference VAR with no error-correction term:

$$\Delta y_t = \Gamma^*_0 + \sum_{i=1}^{p^*} \Gamma^*_i \Delta y_{t-i} + u_t \quad (7)$$

[4] See, e.g. Engle and Yoo (1987). This assumes that r=1. For r>1, this approach consistently estimates one of the cointegrating relationships and so still enables us to assess whether or not r=0.
[5] We have, of course, ignored the implications of the pre-tests we have undertaken.
[6] There is no efficiency loss if the lag lengths are the same in each equation (as then OLS is equivalent to seemingly unrelated regressions estimation) and if the lag lengths we identify for Equation 8 are identical to those that would be used if we considered system 9.

Table 2. *CR ADF* test

Dependent variable	*t*-statistic: Time trend included in CR: Case I	*t*-statistic: Time trend excluded from CR: Case II	Cointegrated?
GDPG	–3.817	–3.243	No
SY	–3.139	–3.182	No
GRNTDY	–2.978	–3.136	No
LOANDY	–4.182	–4.116	No

Notes: The ADF test is applied to $\Delta\hat{Z}_t = \gamma\hat{Z}_{t-1} + \sum_{i=1}^{q}\delta_i \Delta\hat{Z}_{t-i} + \varepsilon_t$, where $\hat{Z}_t$ is the CR OLS residual. In each case q=0 was appropriate. The 5% critical values are (MacKinnon, 1991, p. 275) –5.247 for case I, –4.725 for case II.

Table 3. Some diagnostics

Test	Test statistic	*P*-value
Breusch–Godfrey LM autocorrelation test		
AR/MA(1)	1.247	0.264
AR/MA(2)	3.166	0.205
Breusch and Pagan – Godfrey LM heteroscedasticity test		
Variables: VAR regressors	4.956	0.421
Ramsey's RESET test		
$p = 2$	0.005	0.941
$p = 3$	8.320	0.125
$p = 4$	15.606	0.158
Jarque & Bera's normality test		
Using asymptotic distribution	6.010	0.050
Using bootstrapped distribution	6.010	0.181

Notes: See, e.g. Davidson and MacKinnon (1993), for discussions of these diagnostic tests and appropriate references. The RESET test statistic is given as *pR*, where *R* is the usual statistic. Our regressor set includes lagged dependent variables and so the $R \sim F_{p,df2}$ result no longer holds. We have used that $pR \xrightarrow{d} \chi^2_p$. The bootstrapped *P*-value for the JB test is from 10 000 experiments. All other *P*-values are from the asymptotic distributions.

where $y_t = (GDPG, SY, GRNTDY, LOANDY)'$. The *GDPG* equation, allowing p^* to vary from regressor to regressor, is:

$$\Delta GDPG_t = \gamma^*_0 + \sum_{i=1}^{p_1^*}\gamma^*_{1i}\Delta GDPG_{t-i} + \sum_{i=1}^{p_2^*}\gamma^*_{2i}\Delta SY_{t-i} + \sum_{i=1}^{p_3^*}\gamma^*_{3i}\Delta GRNTDY_{t-i} + \sum_{i=1}^{p_4^*}\gamma^*_{4i}\Delta LOANDY_{t-i} + u_{1t} \tag{8}$$

We test, for instance, that *GRNTDY* 'Granger-causes' *GDPG* by examining the validity of the hypothesis H_0^+: $\gamma^*_{31} = \gamma^*_{32} = \ldots = \gamma^*_{3p_3^*} = 0$ using $W_{H_0^+}$, assuming a limiting $\chi^2_{p_3^*}$ distribution.[5] Unfortunately, our data constraints imply that we must estimate equation 8 rather than the system (7). This may result in efficiency losses as we cannot take into account any contemporaneous correlation between the equation distrubances.[6]

We need p_i^* for each regressor. Various methods have been suggested to estimate p* (see, e.g. the discussion in Lütkepohl, 1993, Chapter 4). We use Akaike's final prediction error (FPE) criterion. Given the data shortage, we consider p_i^* to be at most three (i=1 to 4) and we use the approach of, e.g. Hsiao (1979) and Giles *et al*. (1992). First, set $p_2^* = p_3^* = p_4^* = 0$ and vary p_1^* to find $\hat{P}_1^*$ which minimizes:

$$FPE(p_1^*) = \frac{T+k}{T-k}\,\frac{SSR(p_1^*)}{T} \tag{9}$$

T is the sample size; k is the number of regressors; and $SSR(p_1^*)$ is the sum of squared residuals. Then, with $p_1^* = \hat{p}_1^*$, $\hat{p}_3^* = \hat{p}_4^* = 0$, we vary p_2^* to find $\hat{p}_2^*$ which minimizes $FPE(\hat{p}_1^*, p_2^*)$ and so on until we have determined $\hat{p}_1^*$, $\hat{p}_2^*$, $\hat{p}_3^*$, $\hat{p}_4^*$. This procedure results

Table 4. Granger-causality tests

Test	H_0	H_A	t-statistic	Asymptotic P-value	Granger-causality?
GRNTDY 'Granger-causes' *GDPG*	$\gamma^*_{31} = 0$	$\gamma^*_{31} \neq 0$	0.68	0.496	No
LOANDY 'Granger-causes' *GDPG*	$\gamma^*_{41} = 0$	$\gamma^*_{41} \neq 0$	3.201	0.001	Yes

in $\hat{p}^*_1 = 2, \hat{p}^*_2, \hat{p}^*_3, \hat{p}^*_4 = 1$[7] and the estimated first difference model is (estimated standard errors in parentheses):

$$\Delta GDPG_t = \underset{(1.308)}{-1.340} - \underset{(0.262)}{0.157}\,\Delta GDPG_{t-1} - \underset{(0.228)}{0.440}\,\Delta GDPG_{t-2}$$

$$+ \underset{(0.299)}{0.193}\,\Delta SY_{t-1} + \underset{(159.8)}{108.65}\,\Delta GRNTDY_{t-1} \tag{10}$$

$$+ \underset{(176.9)}{566.38}\,\Delta LOANDY_{t-1} + \hat{u}_{1t}$$

Estimated: 1972 – 90 $R^2 = 0.537$ $\hat{u}_{1t}$ is OLS residual

Table 3 details the outcomes of some diagnostic tests on this model and these suggest that it is reasonable to proceed to our causality tests,[8,9] whose results appear in Table 4. In contrast to Mbaku' s results, ours suggest there exists a causal relationship from foreign aid *loans* to economic growth but not from foreign aid *grants* to economic growth.

IV. CONCLUDING REMARKS

We have shown how recent developments in time series analysis can be used to examine the foreign aid led growth hypothesis. The difference between our results and Mbaku' s (1993) suggest that it is important to test for causality in an appropriate time–series framework. The main limitations of our study appear to be the short-time span of the data and the unavailability of appropriate measures for some of the explanatory variables. Consequently, we could not estimate as detailed a model as desired and accordingly our model may suffer from specification problems which may impact on the properties of the 'Granger-causality' tests. Our analysis clearly illustrates the importance of the data collection part of any econometric study.

ACKNOWLEDGEMENTS

I am grateful to John Mbaku for providing his data on which this study is based, and to David Giles, Les Oxley and Ken Stewart for their helpful discussions and comments.

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[7] Full details of the FPE' s are available on request.

[8] The JB test for normality is marginal using the asymptotic P-value. In this case we approximated the finite sample distribution of the test statistic using a bootstrap experiment (e.g. Efron, 1982; Jeong and Maddala, 1993). The bootsrapped P-value suggests we cannot reject normal errors. Full details are available on request.

[9] Note that contrary to Mbaku (1993), our results suggest no significant autocorrelation. This illustrates the common view that serial correlation is frequently a sign of mis-specification.

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