METHODOLOGICAL NOTE

Economic Development in Africa Report 2024:

Unlocking Africa's trade potential
Boosting regional markets and reducing risks

Methodological Note to chapter 3 of the *EDAR 2024*:

Resilience in connectivity: The potential of regional integration

1. Objectives

The objective of chapter 3, section 3 (Resilience in connectivity: The potential of regional integration) of the Economic Development in Africa Report 2024 (EDAR) is to quantify the effects of the economic and connectivity-related risks on the development of the intra-African value and supply chains through their net impact on industrial productivity. The methodological note discusses the approach used and provides additional results.

2. Data and empirical methodology

Data was used from 2005 to 2022 for 16 COMESA countries (Burundi, Comoros, the Democratic Republic of the Congo, Djibouti, Egypt, Eswatini, Kenya, Libya, Madagascar, Malawi, Mauritius, Rwanda, the Sudan, Uganda, Zambia, Zimbabwe). The selection of both of the time period and countries was determined by data availability for all the key values of interest.

The methodology adopts the conventional Cobb-Douglas aggregate production function:

$$\mathrm{Y} = K^{\alpha}(Al)^{1-\alpha} \quad \text{...(1)}$$

Where *Y* is industrial value added, *K* is capital, *L* is labour and *A* is the productivity of labour. Capital in this model is proxied by the stock of infrastructure; the African Infrastructure Development Index (AIDI) by the African Development Bank. The index has four components: Transport, information and communications technology (ICT), energy and water, and sanitation. However, the industrial value added by the World Bank includes energy (electricity, gas, steam and air conditioning), as well as water and sanitation. As such, these two components of the AIDI are not included as regressors in the model.

In log linear form, (1) becomes:

$$Y_{i,t} = \beta_0 + \beta_1 tpt_{i,t} + \beta_2 ict_{i,t} + \beta_3 l_{i,t} + \beta_4 X_{i,t} + \varepsilon_{i,t} \quad \text{...(2)}$$

Where all the variables are in natural logs, *tpt* is the transport composite index, *ict* is the ICT composite index, *l* is the labour participation rate and *X* is a vector of 3 factors that affect industrial output:

1. Inflation affects the overall cost of production through the general increase in the cost of intermediate inputs.
2. Domestic credit to the private sector (as a percentage of GDP), is used as a proxy for the private sector's access to credit. ε is the white noise error term.
3. Foreign direct investment (FDI).

We assume that infrastructure development affects industrial output with a lag and, therefore, the long-run growth relationship becomes:

$$Y_{it} = \theta_{0i} + \theta_{1i}\, lY_{it} + \theta_{2i} tpt_{i,t} + \theta_{3i} ict_{i,t} + \theta_{4i} credit_{i,t} + \theta_{5i}\pi_{i,t} + \theta_{6i} fdi_{i,t} + \theta_{7i} l_{i,t} + \upsilon_{i,t} \quad \text{......................(3)}$$

i= 1, 2, …, N; t=1, 2, ..., T

Assuming that all variables in equation (3) are I (1) and cointegrated such that the error term is an I (0) for all *i*, then the following Autoregressive Distributed Lag Model (ARDL) (1,1,1,1,1,1) holds for equation (3):

$$Y_{it} = \rho_i + \tau Y_{i,t-1} + \beta_{10}\, tpt_{it} + \beta_{11}\, tpt_{i,t-1} + \beta_{20}\, ict_{it} + \beta_{21i} ict_{i,t-1} + \beta_{30i} credit_{it} + \beta_{31i} credit_{i,t-1} + \beta_{40i}\pi_{it} + \beta_{41}\, \pi_{i,t-1} + \beta_{50i} fdi_{it} + \beta_{51}\, fdi_{i,t-1} + \beta_{60}\, l_{it} + \beta_{61i} l_{i,t-1} + \varepsilon_{it} \quad \text{........(4)}$$

The Error Collection Model (ECM) can be specified as:

$$\Delta Y_{it} = \phi_i\left[Y_{i,t-1} - \theta_{0i} - \theta_{1i} tpt_{it} - \theta_{2i} ict_{it} - \theta_{3i} credit_{it} - \theta_{4i}\pi_{it} - \theta_{5i} fdi_{it} - \theta_{6i} l_{it}\right] - \beta_{11}\, \mathrm{d}Y_{it} - \beta_{21}\, \mathrm{d}tpt_{it} - \beta_{31}\, \mathrm{d}ict_{it} - \beta_{41}\, \mathrm{d}credit_{it} - \beta_{51it}\mathrm{d}\pi_{it} - \beta_{61i}\mathrm{d}fdi_{it} - \beta_{71}\, \mathrm{d}l_{it} - \varepsilon_{it} \quad \text{........(5)}$$

Where:

$$\theta_{0i} = \frac{\rho_i}{1-\tau};\ \theta_{1i} = \frac{\beta_{10i}+\beta_{11}}{1-\tau};\ \theta_{2i} = \frac{\beta_{20}+\beta_{21}}{1-\tau};\ \theta_{3i} = \frac{\beta_{30}+\beta_{31}}{1-\tau};\ \theta_{4i} = \frac{\beta_{40}+\beta_{41i}}{1-\tau};$$
$$\theta_{5i} = \frac{\beta_{50}+\beta_{51i}}{1-\tau};\ \theta_{6i} = \frac{\beta_{60i}+\beta_{61i}}{1-\tau};\ \theta_{7i} = \frac{\beta_{70i}+\beta_{71i}}{1-\tau};\ \Phi_i = -(1-\tau)$$

The Panel Vector Auto Regressive (VAR) model was estimated using a pooled mean group estimator. This model was augmented with the Impulse Response Function (IRF) to visualize the nature of interaction between industrial output and infrastructure variables, as well as ascertains the nature of interaction between the different components of infrastructure.

Thus, it is assumed that on the one hand, good infrastructure is expected to promote industrial growth, albeit with a lag. On the other hand, the growth of industries could also stimulate the development and maintenance of economic infrastructure. Although a potential endogeneity bias cannot be verified completely, endogeneity from reverse causality is addressed in the first lag of all the independent variables.

The estimated panel VAR model is specified as follows:

$$Y_{i,t} = \beta_0 + \sum_{i=1}^{n} \beta_1\, Y_{i,t-1} + \varepsilon_{it} \quad \text{........(6)}$$

Where Y is a 5-vector variable: industrial growth, transport infrastructure, ICT, credit to the private sector, and labour participation rate. This was estimated using a panel VAR estimator. The stability of the model was confirmed before proceeding with the estimation of the orthogonalized IRF, which estimates and maps the response path of a given variable *x* to a standard deviation change in another variable *j*, while holding the responses of all other variables constant. In other words, the orthogonalized IRF was preferred to isolate the unique response path of industrial to standard deviation change in, for example, transport infrastructure. Hence, the response of *x* to a standard deviation in *j* at time *i* is specified as follows:

$$IRF_{x,j}(i) = \psi_{x,j}(i) \qquad (7)$$

We used the Im-Peseran and Shin (IPS) and the Augmented Dickey Fuller (ADF) unit root tests to ascertain the independence of the panels the Akaike Information Criterion (AIC) for optimal lag selection. According to the results in table 2, the first order PVAR was deemed appropriate. The pooled mean group results are provided in table 1.

Table 1: Pooled mean group results

	Error correction term	Transport	ICT	Credit	Inflation	FDI	Labour	Constant
Long-run		0.0553426*** (0.0148213)	-0.0049506*** (0.0009308)	-0.0143279 (0.013524)	-0.0174139*** (0.0038944)	-0.0033875 (0.0036841)	0.1892537 (0.1402585)	
Short-run								
COMESA	-1.284108*** (0.2273138)	-0.2641789 (0.2323543)	0.005618 (0.0090082)	-0.0660189 (0.0759379)	0.004603 (0.0063535)	0.016631 (0.0138572)	2.154107 (1.713619)	-0.979767*** (0.1602438)
Burundi	-0.9731258***	-0.2636062	-0.0003407	0.1572742*	0.0100365	0.0029622**	0.0247364	-0.8552721
Comoros	-0.8801822***	-1.809315	0.0191562	0.0047809	0.0134783***	-0.0334144**	1.098288	-0.7501542
DRC	-4.477538**	-2.629247	0.1221651	-0.8691909	-0.0043266	0.0317016	-7.881936	-3.200274
Djibouti	-1.470957***	-0.015682	0.0057748	0.214427*	0.0104667	0.0330315*	-0.9096049	-0.928207
Egypt	-0.6214767***	0.5263368**	-0.0127875	-0.0601484	0.0028789	0.0169767	0.0416284*	-0.4985242
Eswatini	-1.487476***	-0.0684403	-0.002398	0.1137477	0.0327892	0.0182682	9.368534***	-1.122267
Kenya	-0.4686165***	0.0061402	0.0159515**	0.0303301	-0.0286824***	0.0068743*	2.139436**	-0.3849809
Libya	-1.119928***	0.2582383	-0.0451256	-0.4759291***	-0.041659	0.0583215***	4.194758	-0.9632771

Madagascar	-1.243696***	0.7843538	-0.0359781*	-0.4045076	-0.0356284	-0.0881717**	23.04693***	-0.9174832
Malawi	-0.8966729***	-0.017271	0.0014348	-0.0222784	-0.0198259	-0.0142648	1.312321	-0.6797538
Mauritius	-1.4492633***	1.48775	0.0143512	-0.3036286	0.0183606	0.1667114***	1.443708*	-1.218843
Rwanda	-1.199802***	0.1529992	0.01239*	0.1383607	0.0425654***	0.0027101	-1.865644***	-0.9406759
Sudan	-0.7609517***	0.0070119	0.0103064	-0.019466	0.0293611	-0.0476537	2.452034	-0.4799026
Uganda	-1.466009***	-0.0931571	0.0049894	0.3011678*	0.0178352***	0.0599368***	-3.943111***	-1.164152
Zambia	-1.236655***	-0.0497102**	0.0002116	0.0088287	0.0309627**	0.0155616**	-2.335868	-0.9344591
Zimbabwe	-0.793372**	0.7782338	-0.0202133	0.1299288	-0.0049649	0.0365457	6.279503	-0.6380493

Notes: ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent, respectively. Standard errors are provided in parentheses only for the aggregate estimates. All variables are in logs.

Table 2: Lag order selection

Lag	Coefficient Determination	Hansen's J	J p-value	MBIC	MAIC	MQIC
1	0.999997	42.97317	0.678468	-216.139	-53.0268	-118.889
2	0.999998	22.97796	0.878988	-149.763	-41.022	-84.9298
3	0.999997	7.593557	0.960056	-78.7771	-24.4064	-46.3603

Notes: We adopted the commonly used consistent moment and model selection criterion (MMSC) by Andrews and Lu (2001), which is analogous to the widely used Bayesian information criteria (BIC), the Akaike information criteria (AIC), and the Hannan-Quinn information criteria (HQIC) model selection criteria. These are also referred to as the Modified BIC (MBIC), Modified AIC (MAIC) and Modified QIC (MQIC), respectively as in this table.

3. Stability test for the Impulse Response Function (IRF)

The meaningful Impulse Response Function is conditioned on the stability of the estimated model. This condition was effectively met before proceeding with the computation of the IRF met as shown in Table 3 and Figure 1 below where all the eigen values are below 1.

Table 3: Eigenvalue stability condition

Eigenvalue Real	Eigenvalue Imaginary	Modulus
.9987483	0	.9987483
.8883192	-.0789309	.891819
.8883192	.0789309	.891819
.5634667	0	.5634667
-.2166011	0	.2166011

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All the eigenvalues lie inside the unit circle.
pVAR satisfies stability condition.
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Figure 1: Eigenvalues of the companion matrix