The nexus between infrastructure (quantity and quality) and economic growth in Sub Saharan Africa

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The Nexus between Infrastructure (Quantity and Quality) and Economic Growth

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Abstract

This paper examines the growth effects of infrastructure stock and quality in Sub Saharan Africa (SSA). While previous studies established that the poor state of infrastructure in SSA slows economic growth, there is little evidence on infrastructure quality and a robust analysis on the causal links between infrastructure and economic growth. Using principal components analysis to cluster different infrastructure measures and examining the infrastructure-growth nexus in a Generalized Method of Moments while accounting for heterogeneity in a panel setting, our results reveal strong evidence of a positive effect of infrastructure development on economic growth with most contribution coming from infrastructure stock. The quality-growth effect is weak, thus giving credence to the combined effects of infrastructure stock and quality on growth, especially in regions with moderately high quality, and smaller in those with poorer quality. Among the disaggregated infrastructure components, electricity supply exerted the greatest downward pressure on growth in SSA. Lastly, we find evidence for a unidirectional causality from aggregate infrastructure to growth. A number of policy implications are discussed.

Keywords: Infrastructure stock, Infrastructure quality, Economic growth, Nexus, Causality

1 Introduction

Poor development of infrastructure hinders economic growth in Sub Saharan Africa (SSA) (see Calderon and Seven, 2010; World Bank, 2013). The role of infrastructure in economic growth has been a central theme in policy circles.

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For instance, the African Development Bank (2010) regarded the lack of infrastructure in Africa as a sign of untapped productive potential, which is also a huge investment opportunity. So long as the unmet demand for infrastructure exists, it remains a key restrain on doing business in most African countries which depresses their firms' productivity by roughly 40% (World Bank, 2013).

Infrastructure's role in economic development attracted a great deal of attention in the academic fraternity. The recognition of infrastructure in economic growth has a long standing history that can be traced back to Rostow's growth theory (see Rankin, 2009; Gilman, 2003). In his 1956 paper, Rostow calls for construction of railways or other large overhead capital with long gestation period, which are fundamental for take-off (Rostow, 1956; Rankin, 2009). Consequently, the notion of infrastructure-growth nexus is found in early growth theories though it had not yet received much attention. According to Calderon and Serven (2004), renewed concern with infrastructure can be linked to two main developments worldwide. First, retrenchment of the public sector from its monopoly position in infrastructure provision, following increasing pressure of consolidation and fiscal adjustment and secondly the liberalization of infrastructure industries to private participation.

From an empirical standpoint, the necessity of infrastructure development has earned considerable support. A major empirical work of Aschauer (1989) showed econometrically that much of the decline in productivity experienced by the US in the 1970s followed an earlier downturn in infrastructure investment. When Aschauer pressed this magic button, according to Gramlich (1994: 1177), "beefing up of infrastructure investment became simultaneously the liberal's political war cry of the early 1990s and one of the favorite topics for econometric research,..." However, Gramlich (1994) questioned the contribution of certain categories of infrastructure. He argues that a particular percentage of public stock representing educational buildings, miscellaneous offices, hospitals and conservation should not have significant short-term impact on the supply of national output as it is now quantified. Therefore, some authors (for example, Rubin, 1991) applied various measures of infrastructure and found most explanatory power emerging from the 'core' infrastructure component. Also in Aschauer (1989), the estimated elasticity for the 'core' infrastructure (highways, airports, mass transit, electrical and gas facilities, sewers, water) with respect to productivity in the private business economy was 0.24.

At the same time, however, it is not exactly clear whether it is investment in infrastructure that drives growth or the vice versa. Controlling for endogeneity is thus one of the critical aspects that has been lacking in the earlier literature. A few studies (for instance, Roeller and Waverman, 2001; Calderon and Serven, 2004) have implemented strategies that account for endogeneity of infrastructure. Roeller and Waverman's (2001) results indicated that an increase in telecommunication infrastructure leads to higher growth effects. Calderon and Serven's (2004) Generalized Method of Moments (GMM) estimators show a positive infrastructure-growth effect in 100 countries. Moreover, through his endogenous growth model, Barro (1990) revealed the importance of infrastructure in enhancing the marginal productivity of other capital. Fedderke and

Garlick (2008) identified five channels through which infrastructure influences growth: as a complement to other production factors; a factor of production; a tool of industrial policy; a stimulus to factor accumulation and a stimulus to aggregate demand. In this regard, Bronzini and Piselli (2009) also demonstrated the indirect impact of infrastructure through total factor productivity.

The most critical problem in the infrastructure-growth analysis is failure to account for infrastructure quality (see Fedderke and Garlick, 2008). According to Fourie (2007), both researchers and policymakers still tend to focus on 'more' infrastructure than 'better' infrastructure.

Disentangling the direction of causality between infrastructure and growth is another empirical concern. The direction of causality has not been clear. Some authors (for example, Eberts and Fogarty, 1987; Perkins et al., 2005) found evidence for a bidirectional causality. In contrast, Munnell (1992) found the direction of causation not running from public capital to output but the other way round. Kularatne's (2006) estimations revealed feedback effects between physical infrastructure and output per capita. The actual effect of infrastructure on growth and the causality issue thus become the central empirical challenge (Schiffbauer, 2007, 2008).

Despite a number of studies in this area, the following empirical gaps are identified: (i) accounting for infrastructure quality is still incredibly sparse (ii) addressing the direction of causation between aggregate infrastructure and economic growth is lacking. This study has two major objectives. First, to examine the relationship between infrastructure and economic growth using both aggregate indices of infrastructure stock and quality. Second, to address the infrastructure-growth causation question. Infrastructure stock and quality data for 43 countries in SSA over a period 2000-2014 is obtained from various sources (see Appendix A). We focus on SSA because of a critical shortage of infrastructure stocks and poor quality of the existing infrastructure. According to the African Development Bank (2010), only 26% of the population in SSA had access to electricity in 2008. In terms of road network, only 25% of 204km per 1000km2 of land area was paved; 13 SSA countries had no functional rail networks. Access to fixed line telephones is still below 3%. For Africa at large, the estimated cost of redressing the infrastructure deficit has been estimated to US$38 billion of annual investment and an additional US$37 billion in maintenance (World Bank, 2013). Thus we seek to inform the respective states within SSA on the benefits that can be reaped from infrastructure development and the distress to growth that poor infrastructure quality entails.

This research connects to a number of strands laid in the related literature that accounted for infrastructure quality (for example Calderon and Serven, 2004 & 2010, Calderon, 2009, Loayza and Odawara, 2010). We make three major contributions to the existing literature: Firstly, this study constructs "hybrid" indices that simultaneously capture the aggregate effects of both infrastructure stock and quality. *We assume that infrastructure quality scores may act as weights that can boost (hinder) the effectiveness of infrastructure stock if the quality is better (poor).* When analysing the infrastructure-growth nexus: (i) relying on infrastructure stock alone is not sufficient, and (ii) analysing the stock and quality effects separately may not fully reveal the impact of infrastructure and the challenge is more pronounced in causality testing. Secondly, our aggregate indices account for water, sanitation, electricity, telecommunication and road infrastructures unlike most former studies that focus mainly on the last three categories. Thirdly, unlike the previous studies, we also address the infrastructure-growth causality question. Uniquely in this study, this causality issue is addressed using a 'hybrid' index. The use of an index that accounts for both aggregate infrastructure stock and quality features when addressing causality is lacking. To the best of our knowledge, this kind of analysis has not been carried out.

The remainder of the study is structured as follows: Section two describes the empirical techniques used in this study. Section three presents and discusses the empirical results. Finally, section four concludes.

2 Methodology and Data

2.1 Data

Infrastructure stock and quality data for 43 countries in SSA is gathered for the period 2000-2014.[1] We consider electricity, telecommunication (fixed telephones plus mobile phones), roadways, water and sanitation infrastructures. The infrastructure stocks are standardized across all the countries. The total length of roads in a country is divided by the land area of the country to arrive at *kilometres (km) per square km of land area.* The rest of the infrastructure categories are standardized to take into account the size of population as follows: (i) electricity generation capacity - *thousands of kWh per 1000 persons*, (ii) telecommunication – *fixed telephone plus mobile phone subscriptions per 100 persons*, (iii) water (sanitation) - *number of persons with access to improved drinking water (sanitation) per every 1000 population.* Water and sanitation require further elaboration. The WHO/ UNICEF recognises different sources of water: piped water into dwelling, piped water into yard/plot, public tap or standpipe, tube well or borehole, protected spring and harvested rainwater as "improved" sources. "Improved" sanitation includes flush toilets, piped sewer system, septic tank and flush/pour flush pit latrine. Since we cannot get the actual stock data of these improved sources, we rely on the number of people with access to improved water and sanitation facilities as a proxy.

Our focus is on the "improved" sources because these are the categories that can be directly influenced by public sector investment rather than the "unimproved" sources. We assume the population with access to improved water and sanitation facilities can approximate the stock of these infrastructure

[1] The countries investigated are: Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central Africa Republic, Chad, Comoros, Republic of Congo, Cote d'Ivoire, Democratic Republic of Congo, Equatorial Guinea, Eretria, Ethiopia, Gabon, Gambia, Ghana, Guinea, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome & Principe, Senegal, Seychelles, Sierra Leone, South Africa, Swaziland, Tanzania, Togo, Uganda, Zambia and Zimbabwe.

categories. In this case, the issue of quality is not implied since changes in the population without access to improved facilities is not considered. As a result, our quality measures for water and sanitation are in terms of relative percentage changes in the persons with access to improved facilities. The people with access are compared with those without. An increase in the relative percentage entails improved quality of the service in a country.[2] The quality measures of electricity and roadways are standardized in the same way as their stocks. A proxy for telecommunication quality (*mobile phone quality*) is standardized and presented as *score/100*. Telephone quality is excluded due to several missing observations. Data description and the various sources of the data are shown in Appendix A.

2.2 *Basic econometric model*

Theoretically, we assume a basic production function in which output is function of public infrastructure (G) and a set of standard growth determinants (Z), which takes the following form

$$Y_{it} = f(G_{it}, Z_{it}) \tag{1}$$

where Y_{it} is the output of any country i at time t. Capital and labour are traditionally the key determinants of output from a Cobb Douglas production function position. However, several augmentations of the original Cobb Douglas function have been made. We do not make restrictions about returns to scale following the new growth theories (for instance, endogenous). The endogenous growth theory was developed to go beyond the neoclassical theory by relaxing the diminishing returns assumption or by describing technical change due to specific actions (Stiroh, 2001). In view of equation (1), this study estimates the growth equation on panel data of the form[3]

$$y_{it} = \alpha_t + \phi_i + \psi' y_{i,t-1} + \eta' g_{it} + \theta' z_{it} + \varepsilon_{it} \tag{2}$$

where $y_{i,t-1}$ is the lagged GDP per capita, α_t is the unobserved common factor, ϕ_i is the unobserved country-specific effect parameter, and ε_{it} is the disturbance. Our focus variables (indices of aggregate infrastructure stock, quality and the hybrid) are denotes by g_{it} whereas z_{it} is for control variables that include, human capital, terms of trade, institutional quality, financial depth, trade openness and inflation that have commonly been recognised in the literature.[4]

Given equation (2), the main problem that often plague empirical estimations is identification. Without going deeper, in regression analysis identification problem arises when it is not possible to identify the best estimate of one or more parameters ($\alpha_t, \phi_i, \psi, \eta, \theta$). The question is whether the moment conditions contain sufficient information for the success of estimations (Zsohar, 2010).

[2] This measure of quality controls for possible increase in the number of people with access to improved facilities merely as a results of general rise in population size.

[3] The argumentation involves the realisation of other key factors and alterations of the returns to scale assumptions.

[4] Section 2.3 discusses how the aggregate indices of infrastructure stock and quality are constructed.

Identification demands that there is enough variation in the moment conditions to uniquely identify the parameters. When there are few moment restrictions in the estimation of equation (2) than there are parameters, then the parameters are under-identified. On the other hand, over-identification happens when there more moment restrictions than the parameters. When the moment conditions equals the parameters of interest, the parameters are said to be exactly identified. We briefly highlight some of the threats to identification. In the case of under-identification, no consistent parameters can be estimated (see Nielsen, 2005)[5]. When having an over-identified situation we cannot identify unique values for the vectors of parameters and hence a potential threat to our estimations.[6] In general, the imposition of moment restrictions should not be done arbitrarily for that cannot yield consistent parameters and undermines the estimations. Econometrically, it is imperative to make reasonable identification prepositions. In this study, we implement the GMM that overcomes the threats to identification and allows for consistency.

First, the method of moment estimators may not produce good estimates when the estimators of a single parameter are more than one. In this case, one moment restriction could be satisfied but not the other.[7] The GMM approach overcomes this identification related problem since the GMM estimators are designed to closely meeting all the moment restrictions instead of meeting one of them through the use of appropriate weights. In other words, the rationale of the GMM is that when it is not possible to obtain a solution for the system of equations provided by sample moment restrictions, we compute for θ that draws the sample moments as close to zero as possible (see Zsohar, 2010).[8] The authors also highlighted that, through the application of optimal weighting matrix, the GMM approach such as the two-step is consistent and efficient.

Second, as we demonstrated (see footnote 5) that the correlation between the covariates and error terms can threaten identification and consistency, the GMM mitigate this challenge by employing instrumental variables (IV), which also depend on covariance restrictions and exclusion to produce consistent parameters.[9] Third, the GMM offers basis for empirically testing the over-identifying constraints that helps to see if the data and estimated model are in support.

[5] For instance, assuming a regression with an intercept and x random variable. In this scenario, if $E(x_i\varepsilon_i) \neq 0$ then one remains with only one moment condition ($E(\varepsilon_i)$) but with two parameters (α, β). Though one can pick any value for $\tilde{\alpha}$ and calculate the value for $\tilde{\beta}$ or choose any value for $\tilde{\beta}$ and compute the $\tilde{\alpha}$, such arbitrary parameter estimates fail to satisfy the consistency property and hence a threat.

[6] It becomes problematic to pick among numerous method of moments estimators in overidentifying case.

[7] For example, suppose two method of moment estimators (g_{T1}, g_{T2}) of one parameter ($\tilde{\beta}_i$) with $E(x_i\varepsilon_i) = 0$ and $E(\varepsilon_i) = 0$ held as restrictions, it is often difficult to meet both moment restrictions. It's often that when a particular estimator (e.g. g_{T1}) is used, $E(\varepsilon_i) = 0$ can be satisfied but not $E(x_i\varepsilon_i) = 0$ while the other estimator (g_{T2}) satisfies $E(x_i\varepsilon_i) = 0$ but violates $E(\varepsilon_i) = 0$.

[8] In the case of over-identifying restrictions, the number of estimators converge to the same outcome, in probability, and hence ensuring consistent parameters.

[9] GMM which requires no strong assumptions about the underlying model, it needs only identifying relevant instruments (Jondeau et al, 2004).

2.3 Principal Component Analysis

We found PCA to be the most appropriate method for aggregating the various infrastructure measures. It is a commonly used multivariate approach that allows for data reduction with only the most relevant information retained (Davo et al., 2016; Karamizadeh et al., 2013). Thus, PCA extracts crucial information from a dataset and express it as a set of new orthogonal variables (Abdi and Williams, 2010; Rencher, 2003). Moreover, PCA can reveal latent structures in data (Markaki et al., 2014). In other words, it reveals patterns in data and make it simple to analyse (see Unglert et al., 2016). Finally but not least, PCA lowers the noise in data by selecting the maximum variation and hence automatically neglecting the small variations in the background (Karamizadeh, 2013). Despite these benefits, we are also aware of PCA's problems. If not carefully organised, PCA could generate results that have no economic implications since the technique is pure mathematically based (Zhang et al., 2015). Nevertheless, we believe that PCA can adequately achieve our goal.

The goal of PCA in this study is to identify the principal components that provide greater explanation of the infrastructure dataset. Identifying for instance, the first principal component Z_1 which is a linear combination of X original variables (i.e. standardized infrastructures):

$$Z_1 = u_1 X_1 + u_2 X_2 + ... + u_j X_j \tag{3}$$

such that the maximum variance is attained for possible weighting selection. This linear combination of original variables is defined by a vector of weights $u = (u_1, u_2, ...u_j)$ where the weights are normalized by making the sum of squared values equal to 1 (see Wold, 1987; Calderon, 2009). To determine the number of components to retain, this study considers the components whose eigenvalues are larger than the average of the eigenvalues as a guideline. We also look at the scree plots, which confirm the first guideline. The selected aggregate infrastructure indices are used in infrastructure-growth analysis based on the GMM technique. The GMM is described in full.

2.4 Generalized Method of Moments

The GMM technique is used to examine the effect of aggregate infrastructure stock and quality on economic growth. This approach is adopted for a number of reasons. Unlike the static models, GMM is best suited for dynamic panel data. Most importantly, with GMM one cannot only account for country-specific and unobserved time effects but also for endogeneity of independent variables (Calderon, 2009; Loayza and Odawara, 2010). Among other benefits, unlike the maximum likelihood, econometricians do not need to make strong distributional assumptions (Jogannathan at al., 2002; Arellano and Bond, 1991; Arellano and Bover, 1995; Hansen and West, 2002). The interested variables can be conditionally heteroscedasticity and serially correlated (see Hansen, 1982). Moreover, it can be found that GMM estimators are quite efficient than other popular estimators like the two stage least squares and Ordinary Least Squares

(OLS) when auxiliary assumptions such as homoscedasticity fail (Woodridge, 2001). GMM in econometrics is among the most crucial advancement in the last 35 years but surprisingly its application is still thin. In view of the above, GMM is our estimation technique.

2.4.1 GMM notion

Assume a regression model $y_i = \beta x_i + \varepsilon_i$. Generally the first two moments are $E(y)$ and $Var(y) = E[(y - \mu)^2]$. OLS works under the assumptions that the disturbance has a zero mean ($E(\varepsilon) = 0$) and it is not correlated with each explanatory variable ($E(x_i, \varepsilon_i) = 0$). In nonlinear dynamic models, this is unlikely but rather often characterized by heteroscedasticity and correlation between the covariates and the disturbance ($E(x_i, \varepsilon_i) \neq 0$). In such cases, OLS will not be appropriate but other alternatives exist that include GMM. The application of GMM in the presence of heteroscedasticity was discovered by Cragg (1983), which requires the extraction of additional moment conditions (Wooldridge, 2001). The GMM technique brings up the use of instrumental variables. For instance, z is an instrumental variable of covariate x if it is correlated with x but uncorrelated with the disturbance. Thus, we have $E(x_i, \varepsilon_i) \neq 0$ but $E(z_i, \varepsilon_i) = 0$. Assume X is $n \times k$ matrix of explanatory variables and Z is $n \times l$ matrix of instruments, the moment conditions are: $E(Z', \varepsilon) = 0$, where Z' is a matrix of instruments. The GMM estimator chooses parameter estimates such that the correlation between the error terms and the instruments are as close to 0 as possible by using an appropriate weighting matrix (Eviews, 2015). In particular, it identifies the parameter of interest (θ) that minimizes:

$$\min[(Z'\varepsilon)'C(Z'\varepsilon)] \tag{4}$$

where C is the weighting matrix that weighs every moment condition. An optimal weight is often depicted as $C = \hat{\Omega}^{-1}$, where Ω is the long-run covariance matrix of the moments. Since $\varepsilon = Y - \beta X$, substitute in equation (4) we have: $\min[(Z'(Y - \beta X)'C(Z'(Y - \beta X)$. The optimal θ can be written as:

$$\hat{\theta} = (X'ZCZ'^{-1})X'ZCZ'Y \tag{5}$$

Note that the GMM is a step from the method of moments (MM), famously introduced in the field of econometrics by Hansen (1982) as a remedy to a situation where there are many moments conditions as there are parameters (Zsohar, 2010). When the moment conditions are equal to parameters then GMM=MM. Therefore, GMM is adequate to deal with both a situation where the number of moment conditions equals the number of unknown parameters (just-identified) and where the moment conditions exceed number of parameters (overidentified) (Imbens, 2002).

2.4.2 GMM framework

Panel data are well suited for the investigation of dynamic effects (Greene, 2003). Our estimation is based on the following dynamic (first order) model:

$$y_{it} = \psi y_{i,t-1} + \beta_i' x_{it} + \phi_i + \alpha_t + \varepsilon_{it} \tag{6}$$

where y_{it} is the dependent variable, x_{it} is a vector of explanatory variables, $y_{i,t-1}$, α_t, and ϕ_i ε_{it} are as defined in equation (1). The involvement of $y_{i,t-1}$ in the dynamic model allows for additional information in the system. However, in both fixed and random effects frameworks, the challenge is that the lagged dependent variable and the disturbance are often correlated and this is more vivid in the random effects model (Greene, 2003). This study deals with the problem of correlation and endogenous in the data by adopting a GMM approach developed by Arellano and Bond (1991) and Arellano and Bover (1995) that relies on instrumental variables. The following dynamic model is estimated:

$$\ln \Delta y_{it} = \psi \ln y_{i,t-1} + \theta_i' \ln G_{it} + \lambda_i' \ln Z_{it} + \phi_i + \alpha_t + \varepsilon_{it} \tag{7}$$

Equivalently,

$$\ln \Delta y_{it} = \psi \ln y_{i,t-1} + \beta_i' x_{it} + \phi_i + \alpha_t + \varepsilon_{it} \tag{8}$$

where y_{it} is GDP per capita, G_{it} is a vector of infrastructure variables, Z_{it} is a set of control variables, x_{it} is a set made up of G_{it} and Z_{it} explanatory variables (in logarithm), β_i' is a vector of parameters (includes both θ_i' and λ_i'), and $\ln \Delta y_{it} = \ln y_{it} - \ln y_{i,t-1}$. In order to control for endogeneity of the explanatory variables, Arellano and Bond (1991) suggested the use of appropriate lags of the explanatory variables as valid instruments. Endogeneity of the lagged dependent variable might be caused by the presence of heterogeneity (country-specific effects) (see Hansen and West, 2002). In the spirit of Arellano and Bond (1991), heterogeneity can be eradicated by taking first differences as follows:

$$\ln \Delta y_{it} = (1 + \psi)\Delta y_{i,t-1} + \beta_i' \Delta x_{it} + \Delta\varepsilon_{it} \tag{9}$$

$$\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}; \Delta x_{it} = x_{it} - x_{i,t-1}; \Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i,t-1}$$

Equation 9 may show evidence for correlation between the lagged dependent variable and the disturbance. Consequently, further lagged dependent differences of real GDP per capita ($y_{i,t-2} - y_{i,t-3}, ...$) and/or lagged levels ($y_{i,t-2}, y_{i,t-3}, ...$) are used as valid instrumental variables. According to Arellano and Bond (1991), the covariates matrix may contain a combination of both predetermined (*lags* or *internal instruments*) and strictly exogenous variables. Similar studies (see Calderon and Serven, 2004; Calderon, 2009) considered current and lagged demographic indicators (urban population, population density, labour force) as external instruments. This study relies on internal instruments.

Following Arellano and Bond (1991) we implement GMM (*difference)* to examine the infrastructure-growth nexus. By selecting suitable lagged values of x_{it} and y_{it} as valid instruments and assuming no correlation between them and the time-varying disturbance, we outline a set of moment conditions for the *difference* GMM as follows:

$$E\left[\begin{pmatrix} x_{i,t-1} \\ \downarrow \\ x_{i,t-p} \\ y_{i,t-1} \\ \downarrow \\ y_{i,t-p} \end{pmatrix}(\varepsilon_{it} - \varepsilon_{i,t-1})\right] = 0 \quad ; \quad t \geq 3; p \geq 2 \quad ; \tag{10}$$

N/B: This is a condition for all valid instruments in the differenced equation for period p

Given the moment conditions specified in equation 10, the GMM optimal estimator $(\hat{\delta})$ of the parameter vector of interest (β, α) is:

$$\hat{\delta} = (\tilde{X}'Z\hat{\Omega}^{-1}Z'\tilde{X})^{-1}\tilde{X}'Z\hat{\Omega}^{-1}Z'\tilde{y} \tag{11}$$

$$AV(\hat{\delta}) = (\tilde{X}'Z\hat{\Omega}^{-1}Z'\tilde{X})^{-1} \tag{12}$$

where $\tilde{X}$ is a stacked $n \times k$ matrix of regressors including the lagged dependent variable $y_{i,t-1}$, Z is the $n \times l$ matrix of instrumental variables arose from the moment conditions, ($l > k$, i.e. overidentified), $\tilde{y}$ is the dependent variable stacked in both differences and levels, $\hat{\Omega}^{-1}$ is an estimate of the long-run covariance of the moment conditions[10]. It can be demonstrated that an essential (but not sufficient) condition for obtaining efficient estimate of $\hat{\delta}$ is to set a weighting matrix equal to the inverse of the covariance matrix $(\hat{\Omega}^{-1})$ of the sample moment conditions (Eviews, 2015). At times the lagged levels of the independent variables cannot be strong instruments when the variables are persistent over a period of time (Blundell and Bond, 1998). Therefore, one can apply a *system* GMM which allows for a combination of regressions in differences and in levels (Arellano and Bover, 1995; Blundell and Bond, 1998; Calderon, 2009). However, our instruments based on the *difference* GMM are sufficient to reveal the infrastructure-growth relationship. It is imperative to carry out specification tests. This study employs the Sargan test (based on J-statistic) for overidentifying restrictions, thus examining the validity of the instruments. In addition, the m-statistic test for second-order serial correlation in the first difference residuals is used.

2.5 Dumitrescu-Hurlin (D-H) Non-Causality test

This approach is used to reveal the direction of causality between aggregate infrastructure and economic growth. We chose this modern technique due to

[10] The challenge of the GMM is to obtain an optimal weighting matrix $\hat{\Omega}^{-1}$. It can be shown that $\hat{\Omega}^{-1} = \left(N^{-1}\sum_i Z_i'\hat{v}_i v_i' Z_i\right)^{-1}$ where the v_s are the residuals. For a two-step estimator you replace Z and v with Z^+ and v^+, respectively (see Arellano and Bond, 1991).

its suitability in heterogeneous panels. Dumitrescu and Hurlin (2012) demonstrated a number of benefits associated with this approach, including: (i) controlling for both the heterogeneity of the regression model and heterogeneity of causal relationships, (ii) a test that is based on average individual Wald statistics of Granger non-causality converge sequentially to a standard normal distribution, and (iii) even in the existence of cross-sectional dependence, they demonstrated that their standard panel statistics show good small sample properties using Monte Carlo simulation.

2.5.1 D-H notion

This test realises the major concern associated with panel data, that is, the specification of heterogeneity between cross-section units. Thus the approach accounts for both heterogeneity of the regression model and that of causal link between x and y (Dumitrescu and Hurlin, 2012). This homogenous non-causality (HNC) test (as also known) proposes the null hypothesis of no causal relationship from x to y for all cross-sections; i.e. $H_0 : \beta_i = 0, (i = 1, ..., N)$ against the alternative hypothesis $H_1 : \beta_i = 0, (i = 1, ..., N_1); \beta_i \neq 0; (i = N_1 + 1, N_2 + 2, ..., N)$ where $H_i(N > 0)$ is saying causal relationships occur for at least one cross-section unit. Rejecting H_0 with $N_1 = 0$ implying that infrastructure development (x) Granger causes growth per capita (y) for all the countries in the panel. This entails a homogeneous result. Rejecting H_0 with $N > 0$ shows causal relationships from infrastructure to growth per capita in some of the countries (heterogeneous causal relationships) (see Tugcu, 2014). It is under these heterogeneous circumstances that Dumitrescu and Hurlin (2012) proposed the average of the individual Wald statistics associated with the null of HNC (see Dumitrescu and Hurlin, 2012 for the specifications). The next section presents the empirical results of this study.

3 Results and Analysis

All econometric tests are performed through the use of Eviews 9. We start by constructing our aggregate measures of infrastructure stock and quality using PCA.

3.1 Principal Component Analysis (PCA)

PCA is used to aggregate electricity, roads, telecommunication, water and sanitation infrastructures. All quality measures are in the scale ranging 0-1 (*0 means poorest, 1 is best*)[11]. Both stock and quality of infrastructure measures

[11] Road and electricity quality indicators which are shares of paved roads and electricity distribution losses, respectively, are computationally already in the scale 0-1 but telecommunication, water & sanitation quality scores were originally in the scale 1-100 from their original sources. In line with the related literature (see for instance, Calderon 2009; Calderon and Serven, 2010) we rescaled these other quality indictors to be in the scale 0-1 by dividing each score by 100. Unlike the stock indicators, we denote all quality indicators as scores thus

are transformed to logarithms, and standardized (*have a mean of zero and a unit variance*) to reduce biasness. The results are presented in Table 1. Panels A and B show the two main principal component analyses undertaken in order to construct the aggregate infrastructure stock and quality, respectively. Panel C shows the PCA for institutional quality that combines information on each country's political stability & absence of violence, freedom, governance, and personal safety.

In Table 1, we only show the selected principal components. Though the other components are not shown in the table, the first principal (PC1) is always associated with the largest eigenvalue and proportion of variance. In panels A and C only PC1 is retained. The logic being that only PC1 for infrastructure stock and institutional quality has an eigenvalue greater than the average. Therefore, our chosen guideline suggests that only the first principal components should be retained. However, for infrastructure quality, the same guideline suggests that the second principal component (PC2) also carries significant information. Accordingly, we retain both PC1 and PC2 in panel B. Though Table 1 does not show the eigenvectors, PC1 for infrastructure stock shows positive eigenvectors (loadings) in the range above 0.40. While PC1 for infrastructure quality attaches a very small and negative weight (-0.015) to the quality of electricity. Nonetheless, electricity quality dominates the second aggregate infrastructure with a weight of 0.86. Electricity is therefore the key driving factor in PC2 for infrastructure quality. The aggregate infrastructure variables are graphically presented in Appendix B.

3.2 Descriptive statistics

Table 2 presents the summary statistics of the variables. Our aggregate infrastructure stock (AIS1) and aggregate infrastructure quality (AIQ1), which are based on first principal components are positively skewed, each with kurtosis above the threshold of 3. Contrary to a normal distribution, the distributions of these two aggregate infrastructure measures are characterised by fat tails. Furthermore, the averages for the AIS1 and AIQ1 are negative and close to zero with the standard deviation relatively greater for AIS1.

Unlike the AIS1 and AIQ1, the second measure of aggregate infrastructure quality (AIQ2) is skewed to the left with kurtosis less than 3. Thus, AIQ2 has no fat tails; it shows some form of mean-reverting process. All the aggregate infrastructure variables are not normally distributed since the Jarque-Bera (JB) statistics are statistically significant. In terms of the control variables, the JB test rejects the normality assumption for the terms of trade (LTOT), institutional quality (LINQ), financial depth (LFD), trade openness (LTRA), and inflation (LINF) measures. However, the JB test reveals that the human development variable (LHD) follows a normal distribution. Except for LTRA, all other control variables are negatively skewed with kurtosis above the threshold

having the same measurement unit & hence setting the scores in the same range is much plausible.

of 3 and hence associated with fat tails. Taking the logarithms of the original variables helps us to lower kurtosis and skewness.[12]

3.3 Stationarity tests

Three different tests for panel data are adopted. Table 3 shows the results for stationarity proprieties based on Im, Pesaran & Shin (IPS), ADF-Fisher (ADF, for short), and Levin, Lin & Chu (LLC) panel unit root tests.

The IPS and ADF assume individual unit root process while the LLC test assumes a common unit root process. This study relies more on the first two tests since they account for heterogeneity by assuming individual unit root process. The application of these three tests ensures robustness of the results. We allow for individual intercept for all test equations while the number of lags is set at 1. Without going into detail, except for human development, all series are stationary in first difference across all the three testing models. Some variables are found to be stationary in levels. The LLC test does not reject a common unit root process in human development series even in the first difference while the IPS and ADF reject the presence of individual unit root.[13] It is not econometrically plausible to work with non-stationary data for this may threaten the identification of parameters and leads to spurious results. To solve this problem our regressions apply the first differences of the variables and hence guarantees the use of stationary data.[14] This enables us to examine the growth effects in terms of change in growth per capita from a unit change in aggregate infrastructure.

3.4 Interpretation of key results

All the GMM estimates are performed including an intercept and periodic dummies but the coefficients are not presented in the Tables. We apply only internal instruments across all the models. AIS1 and AIQ1 represent aggregate infrastructure stock and aggregate infrastructure quality based on the first principal components. AIQ2 is the aggregate infrastructure quality based on the second principal component. HII is the hybrid infrastructure index that captures both the aggregate stock and quality effects of infrastructure. Quality might act as weight for the infrastructure stock; proposing that poor quality dampens

[12] Note that the presents of fat tailed and skewed variables violates normality assumptions which may possibly threaten identification when failure to satisfy certain moment restrictions is linked to non-normality in the distribution of data. However, this is not going to be a problem for we adopt the GMM technique that does not require any distribution assumptions (see Hansen and West, 2002). The violations of normality assumptions are disturbing if the test is norm-referenced (JALT, 1997). In addition, the interpretation of kurtosis and skewness statistics must be done in terms of the purposes and types of tests performed. For our tests, this will not negatively affect our ability to find the impact of infrastructure on growth and the direction of causality.

[13] Though not indicated in the Table, the LLC approach suggests human development is stationary in the second difference.

[14] We only employ the second difference of human development (D2LHD) for the sake of stationarity confirmation across all three unit root tests since it is I(2) based on the LLC test.

the potential benefits obtainable from infrastructure stock. LHD, LTOT, LINQ, LFDP, LTRA and LINF are the logarithms of human capital, terms of trade, institutional quality, financial depth, trade openness and inflation, respectively.

3.4.1 SSA - Entire sample

Four striking results are shown in Table 4: First, based on the first principal components, both AIS1 and AIQ1 show positive and significant growth effects in SSA. The annual contribution of infrastructure stock to growth per capita is 47 basis points while infrastructure quality contributes 10 basis points over a 15 year period. Thus, infrastructure has been a key factor that underpins economic growth in SSA. This is expected given the direct effect of public infrastructure in boosting productivity of private capital and as a complement to private investment (see Agenor and Moreno-Dodson, 2006). Our results are consistent with the findings of Calderon (2009) and Calderon & Serven (2004, 2010) who considered aggregate indices of both infrastructure stock and quality.

Second, the qualitative-growth link is found to be weaker. While infrastructure stock can lead to 0.47% rise in growth per capita, quality development can increase growth by only 0.10% per year. According to Calderon and Serven (2004) this might be linked to limitations of the quality measures or strong correlation between quantity and quality measures. Third, it is interesting that the joint effect of aggregate index of stock and quality (33 basis points) is less than the stock-growth effect. This outcome is not surprising given the poor quality of infrastructure services in SSA. Thus, the results of the hybrid index suggest that poor infrastructure quality in SSA dampens the growth effect of the existing infrastructure stock.

Fourth, the coefficient for the second measure of aggregate infrastructure quality (AIQ2) is negative and significant. This means quality development (based on the second principal component) reduces growth per capita by 1 basis point. We believe this is due to the poorest quality of electricity services in SSA since AIQ2 index is heavily dominated by electricity which has a weight of 0.86. Therefore, deterioration in electricity services is the key obstacle that lessens economic growth (see Calderon, 2009). First, poor electricity quality as signified by high levels of transmission and distribution losses (technical losses), including pilferage (non-technical losses) might negatively affect economic growth in two ways: (i) reducing electricity final consumption and (ii) increasing the cost of production. Poloamina and Umoh (2013) demonstrated that electricity transmission and distribution losses are among the key factors that lower the levels of electricity consumption in SSA. Second, small power plants that are common in SSA are missing economies of scale that may improve the quality of electricity service. While large power plants are most cost-effective, Africa is dominated by small-scale power systems that result in higher distribution and transmission costs (African Development Bank, 2013). The African Development Bank indicated that these high cost and tariffs force governments to subsidise electricity consumption. Third, electricity might overwhelm other infrastructure sectors, thus, we further justify our suspicion that electricity quality could be the reason behind a negative coefficient of AIQ2 by removing electricity from the aggregate measure of infrastructure. We present the results for this additional analysis in Appendix A (See Table A1). In this case, only the first principal component is retained; the quality-growth effect without electricity is positive (0.20%) and higher than both previous quality effects (0.10% & -0.01%) in Table 4. The current higher positive coefficient may suggest the absence of the negative effect previously from electricity quality. It is therefore plausible for high levels of electricity distribution losses in SSA to have negative growth effects.

While Calderon's (2009) results predicted negative output elasticities of electricity quality in NA, SNA and WA, our results depict a similar implication where a negative effect is only associated with a quality index that puts more weight on electricity service. This analysis is able to pick up the major reason for a negative growth effect by considering the weights of the individual infrastructures. We do not expect the qualities of all the infrastructure categories to assume a negative effect on growth. For example, in practice, we have seen improvements in the quality of telecommunication, water and sanitation in most African countries while the widespread outages of electricity are worrisome. Effective telecommunication facilitates economic growth by allowing information sharing and conduct of trade-related businesses among economic agents. Improved drinking water and sanitation facilities can reduce the chances of people getting sick due to dirty water and poor sanitation. Such health enhances the productivity of workers. Amongst the five infrastructure categories, deterioration in electricity quality (power losses) is expected to have a major negative growth effect. As we witness electricity blackouts in most Sub Saharan countries, it is conceivable that the AIQ2 which is dominated by electricity quality can dampen economic growth. On the other hand, AIQ1 with sizable weights of telecommunication (0.43), water (0.56), sanitation (0.51) and road (0.49) quality measures and little of electricity (-0.02) shows positive growth effect as the electricity effects are less represented.

In addition, our results suggest that human development, favourable terms of trade, enhanced institutional quality and trade openness have positive growth effects in SSA. Most of the coefficients are highly significant across all the models. Education has been the driving force for human development in Africa (Escosura, 2013). In empirical studies some use different measures of education, others use human development (which is comprised of health) as proxies for human capital. Whatever proxy is used, human capital tend to have a positive effect on economic growth. The positive effect of terms of trade on growth is consistent with similar studies (for example, Calderon 2009, Calderon and Serven 2004 & 2010, Loayza and Odawara, 2010) that focus on Africa. Our results agree with the conventional wisdom that trade liberalization facilitates economic growth. It broadens the market for trade, enhancing cross-border transfer of knowledge and technology, and allows a greater pool of productive resources. Most importantly, improved institutional quality enables a favourable investment atmosphere, reduces corruption and ensures better use of resources.

Only inflation and financial depth have negative effects on growth per capita.

The negative effect of inflation is expected because price instability makes it difficult for investors to plan, increases the risk of investment, and erodes the wealth of fixed income earners, among other adverse outcomes. Financial development is usually expected to have a positive growth effect but this study proves otherwise (see also Kumar et al, 2015). This entails the poor development of the financial system in SSA. The banking and financial systems remain underdeveloped. In particular, the banking systems are highly concentrated and often inefficient at financial mediation, which presents one of the key obstacles to economic activity (European Investment Bank, 2013). In Table 4, the lagged GDP per capita has a positive but minor impact on the current GDP per capita. Finally, we cannot reject the null hypothesis of correct specification across all models as suggested by the J-statistic (Sargan) test of overidentifying restrictions. Moreover, the m-statistic indicate that the hypothesis of absence of second-order serial correlation cannot be rejected. The specifications passed diagnostic test and hence validate our results. This is the same across all our GMM results in every table.

3.4.2 Sub-regional effects

We perform additional GMM tests for the sub-regions within SSA. The results for the impact of infrastructure stock and quality on growth are essentially the same as those in Table 4. Therefore, much emphasis is on the comparison between the magnitudes of infrastructure contribution among the sub-regions. Table 5 presents the effect of aggregate infrastructure stock.

The results indicate a greater contribution of infrastructure stock on the growth rate of Central Africa (CA), followed by Southern Africa (SNA), East Africa (EA) and West Africa (WA). Over a 15 year period investigated, infrastructure stock yields 0.75% of growth per annum in CA, 0.47% in SNA, 0.46% in EA and 0.38% in WA. This means the rate of return per unit of infrastructure investment is higher in CA, a region with the lowest level of infrastructure stock (see Appendix B, Figure B1). This is conceivable, for instance, when the effect of extra 100 kilometres of road is more notable in a nation with very poor road network and less where the existing network is better. Due to relatively critical shortage of infrastructure in CA, investment in infrastructure may focus more on creating new routes and increasing the number of persons with a phone.

The impact of aggregate infrastructure quality (based on the first principal component) is presented in Table 6. The estimates are positive and statistically significant across all the sub-regions. The benefit of infrastructure quality is relatively higher in CA (0.37%), then WA (0.24%), EA (0.14%) and SNA (0.12%). It is amazing since infrastructure quality suggests a huge growth impact in the region with the lowest quality level (CA) and less in that with better quality (SNA). Generally, the results reveal the necessity of infrastructure quality development in SSA though it may not yield as much benefits as infrastructure stocks.

Table 7 shows the results based on our second measure of aggregate infrastructure quality (AIQ2). The measure is based on the second principal component.

As previously mentioned, AIQ2 is heavily dominated by electricity service. As a consequence, an explanation of the coefficients of AIQ2 should be greatly linked to the behaviour of electricity quality in SSA. The coefficients for the AIQ2 are negative and statistically significant in three of the regions (SNA, WA and CA) while the coefficient for EA is positive and significant. One interpretation is that electricity quality developments reduce growth per capita in SNA by roughly 9 basis points while growth rates in WA and CA decline by 7 and 2 basis points, respectively. We have already explained that the negative coefficients are mainly connected to deterioration in electricity quality. However, the contribution is positive in EA. Calderon (2009) also found developments in electricity services to have negative growth effects in SNA and CA while EA benefited.

The joint (or combined) effects of the aggregate infrastructure stock and quality are shown in Table 8. The contribution is highest in SNA then followed by EA. It raises growth per capita in SNA and EA by 0.78% and 0.73%, respectively. Growth per capita is lowest in WA (0.32%). Remarkably, the joint effect is greater than the contribution of infrastructure stock alone in the regions with relatively high infrastructure quality (SNA and EA) and smaller in the regions with the lowest infrastructure quality (WA and CA) (see Appendix B, Figure B2). Though the results in Table 5 show the highest stock contribution in CA (0.75%), the joint effect is lower (0.51%). We believe this is due to the poorest level of infrastructure quality in CA. This validates our assumption that quality may act as weight that can boost (hinder) the effectiveness of infrastructure stock if the quality is reasonable (poor).

3.4.3 Direction of causality

This section is motivated by fact that the existence of a strong relationship between infrastructure development and economic growth does not essentially entail a causal relationship (see Yoo, 2006). Police wise, the knowledge about causality has vital insights. A unidirectional relationship from infrastructure to economic growth implies that reducing infrastructure development could cause a decline in economic growth. On the other hand, a unidirectional causality running from economic growth to infrastructure development implies that policy measures for lessening infrastructure development could be adopted with no or little negative growth effects. A bilateral causality suggests that a rise in the development of infrastructure induces economic growth while higher growth may require more infrastructure.

Table 9 shows the results of the direction of causality. The p-values of the causality tests performed on the first differences of the joint aggregate infrastructure and economic growth are shown. In panel A, we reject (at 5% significance level) the hypothesis that ΔJoint-AINFRA does not homogeneously cause ΔGDP at both lags 1 and 2 but we fail to reject in the opposite. Thus, changes in the combined infrastructure (i.e. stock and quality of telecommunication, electricity, roads, water and sanitation) lead to changes in GDP per capita but not the other way round. These results suggest a unidirectional causality running from infrastructure development to economic growth. The effects of infrastructure development in the last two years will still have impact on current GDP. *Most crucial herein is that, unlike the usual infrastructure-growth causality literature, this is a synchronised effect of both aggregate infrastructure stock and quality.* Panel B shows causality results when aggregate infrastructure stock and quality are analysed separately. Surprisingly, the estimation entails no causality between infrastructure stock and growth in both lags. We only detect causality from infrastructure quality to GDP per capita in the initial lag.

Based on the causality analysis of this study, the most striking result is that strong evidence for causality is found when quantity and quality features of infrastructure are jointly captured compared to when they are separately applied. We believe it is useful to employ a hybrid index that accounts for both infrastructure stock and quality when performing causality tests. The advantage being that not only the magnitude of infrastructure matter but also their efficiency. The use of infrastructure stock alone (as common in literature) might fail to detect causality. We assume that the power to discover causality from infrastructure stock to economic growth in this study weakens due to missing information regarding the quality of the infrastructure stocks in SSA, *ceteris paribus.*

3.5 Implications of results

From a policy perspective, investment in both public infrastructure stock and quality is warranted as justified by the positive growth effects of infrastructure stock and quality. For growth purpose, infrastructure development is one of the drivers of economic growth. This result is relevant to policy makers as the contributions of other factors to economic growth may change overtime. For instance, the relevance of labour as a key determinant of economic growth has been weakening due to rise in labour-saving technologies (see Streimikiene and Kasperowicz, 2016). Therefore, a continuous investigation of other key growth factors is desirable, of which herein public infrastructure has proven relevant.

Furthermore, this outcome is relevant to ordinary people who are part of the end users of infrastructure. Effective use of infrastructure by the public can aid growth per capita in various ways. Firstly, the duration of infrastructure is prolonged when the public carefully use the assets. Secondly, to reap more from infrastructure quality the public should not vandalise the existing infrastructures, which is often a problem in Africa. When malicious destruction of infrastructure (e.g. public tapes, electricity & telephone cables) is avoided, it reduces the cost of maintenance and focus on upgrading. Our results therefore are not only vital to policy makers but even to the layman.

To both researchers and policy makers, the hybrid index results suggest that it is possible to exaggerate the benefits obtainable from aggregate infrastructure stocks when the stocks of such infrastructure are miserable. In practice, it is tempting to make projections solely based on infrastructure stock in an economy.

However, to have a better picture, it seems imperative to jointly incorporate the quality effects. The quality of infrastructure often deteriorates over a period of time and hence persistent maintenance and upgrading is required. As estimated by the World Bank, the US$37 billion of annual investments for infrastructure maintenance and operations is justified if African states are to apprehend the potential benefits of their infrastructure stocks.

One of the remarkable implications is derived from the negative coefficient of the AIQ2 which is dominated by electricity quality. This result suggests that the power outages that have been common in most SSA states are counterproductive. For instance, electricity distribution losses can affect the performance of other infrastructures such as mobile & telecommunication connection, and lead to temporary stoppages of industrial production. This informs the respective governments in SSA on the consequences of power cuts, a problem that needs much focus. Caution must be taken when implementing electricity saving strategies (e.g. load shedding) which may negatively affect economic activities. Uninterrupted power supply is crucial for the future growth rate of Africa. This may entail improving existing electricity supply channels while diversifying the sources of supply, especially in countries that rely heavily on hydro power.

In terms of sub-regions, the results of the hybrid indices versus the stocks entail something significant. Through the hybrid indices (stock and quality) we demonstrated that the combined effect will be higher than the stock effect in regions with relatively high infrastructure quality and lower than in regions with poorer infrastructure. It implies that regressions based on stocks alone may exaggerate the contribution of infrastructure stock if the quality is bad while reasonable quality shows an additive effect. From researchers' viewpoint, this entails the importance of applying hybrid indices, which tend to be more robust in both the infrastructure-growth nexus and causality.

Based on the control variables, measures such as export incentives are supported in SSA to constantly improve the performance of terms of trade. Moreover, since our institutional quality index is an aggregate of governance, political stability and absence of violence, freedom and personal safety, results suggest that an improvement in these measures enhances economic growth. Enhanced institutional qualities provide a sound environment for investments. Political stability and good governance do not only attract foreign direct investment but improve also the productivity of local investments. Furthermore, political stability, degree of freedom, governance and personal safety are often used to determine if a country is less risky and profitable to invest (see Perera and Lee, 2013). From a policy position, the results infer that African governments should focus more on the improvement of institutional qualities. Dealing with respect of human rights, rule of law and corruption are still central in SSA. The understanding of the pivotal role of institutional qualities remains fundamental to the growth trajectory of Africa. The institutional quality results are also relevant to the ordinary people regarding the merits of public investments when the politicians are held accountable for their decisions.

4 Concluding remarks

Sub Saharan Africa is facing critical shortage of infrastructure. It has been held as one of the key factors that slows economic growth in the region. The problem is amplified by the poor quality of existing infrastructure. This study examined the infrastructure-growth relationship and the causality between aggregate infrastructure and economic growth in SSA. We considered both aggregate stock and quality measures of infrastructure. The aggregate stock and quality effects are further jointly captured in form of 'hybrid' indices. Unlike the common causality approaches in the extant literature, we apply a 'hybrid' index to address the infrastructure-growth causation question. The infrastructure categories considered are: electricity, telecommunication, roadways, water and sanitation. PCA is used to aggregate these infrastructure measures. The infrastructure-growth nexus is investigated using the Generalized Method of Moments. The Dumitrescu-Hurlin test that controls for heterogeneity in panel data is adopted to detect the direction of causality.

Our GMM results reveal strong evidence for a positive effect of infrastructure development on economic growth with most contribution coming from infrastructure stock. The quality-growth effect is weak. While the quality effects are weaker, we realized that the combined effects of stock and quality are larger than the stock effects alone in the regions with moderately high quality and smaller in those with poorer quality. The implication is that the infrastructure-growth nexus analysis based on infrastructure stock alone may exaggerate or underestimate the effects depending on the quality of existing stocks. In such cases, we believe a hybrid index is superior. One of the aggregate infrastructure quality measures which is greatly composed of electricity generally shows a negative growth effect. It entails the intensity of poor electricity services that impede economic growth in SSA. This is witnessed by rampant electricity power failures (or cuts) in most Sub Saharan countries. In terms of causality, we find evidence for a unidirectional causality from aggregate infrastructure to growth. This is mainly based on the joint effect of aggregate stock and quality. When these effects are separated, we hardly detect causality.

Based on the findings of this study, it is vital to account for both infrastructure stock and quality when analyzing the infrastructure-growth nexus, and addressing the causation question. We recommend researchers to focus more on hybrid indices that allow the stock and quality effects to be jointly captured. Policy wise, we argue the states in the SSA to boost their infrastructure expenditures. This includes considerable investments in the maintenance and improvement of infrastructure quality. Dealing with widespread outages of electricity should be the central focus Generally, poor quality of infrastructure stocks in SSA diminishes the benefits of such stocks. Our results could serve as one of the policy guidelines for the SSA states and other economies in a similar scenario.

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Table 1
Eigenvalues for the selected components

	Eigenvalue	Proportion	Cumulative
Panel A: PCA for infrastructure stock			
PC1	2.913	0.583	0.583
Panel B: PCA for infrastructure quality			
PC1	2.368	0.474	0.474
PC2	1.149	0.230	0.703
Panel C: PCA for institutional quality			
PC1	2.917	0.730	0.729

Note: The eigenvalues show the importance of each principal component.

Table 2
Summary statistics

	Mean	Med	Max	Min	Std. Dev	Skewness	Kurtosis	JB	Obs
AIS1	-0.00	-0.00	4.87	-4.16	1.71	0.45	3.38	25.92***	645
AIQ1	-0.00	-0.29	4.90	-2.76	1.54	0.95	3.78	112.97***	645
AIQ2	0.00	0.26	3.56	-2.70	1.07	-0.35	2.83	13.79***	645
LGDP	6.79	6.51	10.10	4.69	1.17	0.76	2.79	63.78***	645
LHD	3.94	3.95	4.46	3.25	0.24	-0.11	3.13	1.78	645
LTOT	4.68	4.61	5.56	3.05	0.35	-0.68	6.93	434.67***	602
LINQ	-0.00	-0.09	4.29	-4.77	1.71	-0.15	2.68	5.25*	645
LFDP	2.63	2.67	5.08	-1.62	0.88	-0.16	4.75	80.56***	612
LTRA	4.27	4.24	5.86	3.04	0.48	0.34	2.91	12.25***	633
LINF	1.74	1.89	6.24	-3.22	1.03	-0.30	5.00	112.79***	625

Note: *** denotes rejection at 1% significance level. AIS1, AIQ1 and AIQ2 are the aggregate infrastructure measures (in logs). LINQ is the first principal component of several institutional quality measures in logs.

Table 3
Panel stationarity tests

	Im, Pesaran & Shin (IPS)		ADF-Fisher (ADF)		Levin, Lin & Chu (LLC)	
Variable	Level	Fist Difference	Level	First Difference	Level	First Difference
AIS1	-0.021	-2.304***	80.947	116.402**	-8.999***	-1.881**
AIQ1	10.058	-4.610***	14.495	152.730***	5.173	-6.985***
AIQ2	5.561	-9.242***	39.914	244.821***	1.009	-10.095***
LHD	3.276	-7.056***	45.663	195.567***	-0.916	-0.823
LGDP	-0.018	-7.794***	83.681	212.910***	-7.781***	-9.741***
LTOT	-0.540	-9.077***	82.760	238.083***	-4.426***	-13.009***
LINQ	-0.424	-8.879***	88.893	237.418***	-1.890**	-4.607***
LFDP	1.784	-5.942***	74.981	171.378***	-3.533***	-7.015***
LTRA	-1.935**	-11.338***	114.993**	279.635***	-4.402***	-17.643***
LINF	-4.949***	-10.441***	156.047***	275.676***	-4.128***	-11.639***

Note: *** and ** indicate significance at 1% and 5%, respectively. LLC statistic for LHD becomes significant at second difference. We include individual intercept for all test equations with the maximum number of lags set at 1.

Table 4

Aggregate infrastructure effect - SSA

Independent Variables	Model 1 (**AIS1**) (*Stock effect*)	Model 2 (**AIQ1**) (*Quality 1 effect*)	Model 3 (**AIQ2**) (*Quality 2 effect*)	Model 4 (**HII**) (*Joint effect*)
Aggregate Infrastructure				
Infrastructure stock (PC1)	0.472***	----	----	----
Infrastructure quality (PC1)	----	0.102***	----	----
Infrastructure quality (PC2)	----	----	-0.012**	----
HII (AIS1 X AIQ1)	----	----	----	0.327***
Control variables				
1st Lag GDP per capita	0.076***	0.080***	0.088***	0.058***
LHD	0.216***	0.334***	0.339***	0.393***
LTOT	0.383***	0.476***	0.463***	0.428***
LINQ	0.351***	0.123*	0.122**	0.241***
LFDP	-0.208***	-0.080***	-0.062***	-0.098***
LTRA	0.118***	0.038***	0.031***	0.038***
LINF	-0.034***	-0.017***	-0.016***	-0.036***
Number of Obs.	555	555	555	555
Number of countries	43	43	43	43
Diagnostic tests				
(1) J-statistic:	40.590	39.109	38.885	39.687
(P-value)	(0.203)	(0.251)	(0.259)	(0.231)
(2) m-Statistic(2nd order):	-0.828	-0.744	-1.539	-1.059
(P-value)	(0.408)	(0.457)	(0.124)	(0.290)

Note: GDP per capita is the dependent variable. '***', '**' & '*' imply significance at the 1%, 5% & 10%, respectively.

Table 5

Regional stock effects

Independent Variables	Southern Africa (SNA)	East Africa (EA)	West Africa (WA)	Central Africa (CA)
Aggregate Infrastructure				
Infrastructure stock (1st principal component)	0.4705***	0.457**	0.381***	0.749***
Control variables				
1st Lag GDP per capita	0.069***	0.092***	0.121***	0.127***
LHD	0.345***	0.467***	0.306***	0.461***
LTOT	0.437***	0.628***	0.524***	0.465***
LINQ	0.109***	-0.008	0.102	0.046
LFDP	-0.089***	-0.098***	-0.126***	-0.143***
LTRA	0.079***	0.012	0.043**	0.019
LINF	-0.018***	-0.029***	-0.015**	-0.012*
Number of Obs.	381	367	376	376
Number of countries	43	43	43	43
Diagnostic tests				
(1) J-statistic:	39.516	37.560	38.560	38.819
(P-value)	(0.237)	(0.268)	(0.271)	(0.261)
(2) m-Statistic(2nd order):	-1.214	-1.078	-1.487	-1.613
(P-value)	(0.225)	(0.281)	(0.137)	(0.107)

Note: see Table 4 footnotes and Appendix A (Table A2) for the countries that fall within each sub-region.

Table 6

Regional quality effects (AIQ1)

Independent Variables	Southern Africa (SNA)	East Africa (EA)	West Africa (WA)	Central Africa (CA)
Aggregate Infrastructure				
Infrastructure quality	0.120***	0.140*	0.240**	0.372***
(1st principal component)				
Control variables				
1st Lag GDP per capita	0.129***	0.108***	0.119***	0.103***
LHD	0.493***	0.498***	0.332***	0.342***
LTOT	0.424***	0.433***	0.554***	0.425***
LINQ	-0.066	-0.048	-0.014	0.123
LFDP	-0.102***	-0.165***	-0.078***	-0.063***
LTRA	0.052***	0.002	0.025*	0.063***
LINF	-0.0079*	-0.007*	-0.015*	-0.017**
Number of observations	419	418	381	381
Number of countries	13	8	14	8
Diagnostic tests				
(1) J-statistic:	40.437	41.179	38.418	37.848
(P-value)	(0.207)	(0.185)	(0.276)	(0.298)
(2) m-Statistic(2nd order):	-1.256	-0.371	-0.711	-0.860
(P-value)	(0.209)	(0.711)	(0.477)	(0.390)

Note: see Table 5 footnotes. All the five infrastructure categories carry almost equal weights in AIQ1.

Table 7

Regional quality effects (AIQ2)

Independent Variables	Southern Africa (SNA)	East Africa (EA)	West Africa (WA)	Central Africa (CA)
Aggregate Infrastructure				
Infrastructure stock	-0.093**	0.144**	-0.069***	-0.017***
(2nd principal component)				
Control variables				
1st Lag GDP per capita	0.081***	0.118***	0.141***	0.134***
LHD	0.393***	0.471***	0.365***	0.366***
LTOT	0.449***	0.662***	0.536***	0.542***
LINQ	0.134**	-0.048	0.034	0.077
LFDP	-0.085***	-0.070*	-0.062***	-0.126***
LTRA	0.046***	0.013	0.062***	0.042**
LINF	-0.017***	-0.009**	-0.012**	-0.018**
Number of Obs.	381	367	376	376
Number of countries	13	8	14	8
Diagnostic tests				
(1) J-statistic:	39.327	36.508	38.719	39.101
(P-value)	(0.244)	(0.309)	(0.265)	(0.251)
(2) m-Statistic(2nd order):	-0.666	-1.445	-1.584	-0.557
(P-value)	(0.505)	(0.148)	(0.113)	(0.578)

Note: see Table 5 footnotes. AIQ2 is heavily composed of electricity infrastructure quality.

Table 8
Regional joint effects

Independent Variables	Southern Africa (SNA)	East Africa (EA)	West Africa (WA)	Central Africa (CA)
Aggregate Infrastructure				
Hybrid Infrastructure (AIS X AIQ1)	0.779***	0.732***	0.316***	0.508***
Control variables				
1st Lag GDP per capita	0.065***	0.100***	0.119***	0.101***
LHD	0.337***	0.355***	0.487***	0.293***
LTOT	0.439***	0.465***	0.419***	0.483***
LINQ	0.113***	0.032	-0.067	0.159
LFDP	-0.073***	-0.066***	-0.096***	-0.093***
LTRA	0.044***	0.022	0.062***	0.057***
LINF	-0.018***	-0.014**	-0.010**	-0.020***
Number of observations	381	381	419	376
Number of countries	13	8	14	8
Diagnostic tests				
(1) J-statistic:	39.975	37.103	38.980	38.083
(P-value)	(0.222)	(0.328)	(0.256)	(0.289)
(2) m-Statistic(2nd order):	-0.557	-0.297	-1.311	-1.580
(P-value)	(0.578)	(0.767)	(0.190)	(0.114)

Note: see Table 5 footnotes.

Table 9
Dumitrescu-Hurlin non-causality results

Null hypothesis:	W-Stat.	Zbar-Stat.	P-value.
Panel A: Joint Aggregate Infrastructure			
Lag 1			
Δ GDP does not homogeneously cause Δ Joint_AINFRA	1.118	-0.399	0.690
Δ Joint_AINFRA does not homogeneously cause Δ GDP	1.964	2.162	**0.031**
Lag 2			
Δ GDP does not homogeneously cause Δ Joint_AINFRA	2.365	-0.666	0.505
Δ Joint_AINFRA does not homogeneously cause Δ GDP	4.300	2.301	**0.021**
Panel B: Stock & Quality separately			
Lag 1			
Δ GDP does not homogeneously cause Δ Infrastructure Stock	1.171	-0.240	0.810
Δ Infrastructure Stock does not homogeneously cause Δ GDP	1.549	0.905	0.366
Δ GDP does not homogeneously cause Δ Infrastructure Quality	1.498	0.750	0.453
Δ Infrastructure Quality does not homogeneously cause Δ GDP	2.291	3.153	**0.002**
Lag 2			
Δ GDP does not homogeneously cause Δ Infrastructure Stock	2.463	-0.517	0.605
Δ Infrastructure Stock does not homogeneously cause Δ GDP	3.831	1.581	0.114
Δ GDP does not homogeneously cause Δ Infrastructure Quality	2.282	-0.794	0.427
Δ Infrastructure Quality does not homogeneously cause Δ GDP	3.746	1.450	0.147

Note: Joint_AINFRA is the joint aggregate infrastructure index that combines both aggregate infrastructure stock and quality. GPD is the gross domestic product per capita.

Appendix A: Additional results and data information

Table A1
Effect of aggregate infrastructure - excluding electricity

Independent Variables	Model 1 (**AIS1**) (*Stock effect*)	Model 2 (**AIQ1**) (*Quality effect*)	Model 3 (**HII**) (*Joint effect*)
Aggregate Infrastructure			
Infrastructure stock (PC1)	0.294***		
Infrastructure quality (PC1)		0.202***	
HII (AIS X AIQ1)			0.067***
Control variables			
1^{st} Lag GDP per capita	0.076***	0.068***	0.065***
LHD	0.353***	0.407***	0.974***
LTOT	0.495***	0.460***	0.426***
LINQ	0.114*	0.086	0.0002
LFDP	-0.151***	-0.085***	-0.094***
LTRA	0.064***	0.103***	0.048**
LINF	-0.016***	-0.016**	-0.013**
Number of observations	376	381	419
Number of countries	43	43	43
Diagnostic tests			
(1) J-statistic:	38.362	38.015	40.762
(P-value)	(0.278)	(0.291)	(0.232)
(2) m-Statistic(2^{nd} order):	-0.982	-1.605	-0.024
(P-value)	(0.326)	(0.109)	(0.981)

Note: see Table 5 footnotes. Unlike the previous analysis, electricity is excluded from the aggregates indices to see if it does overwhelm other infrastructure sectors (telecommunication, roads, water & sanitation).

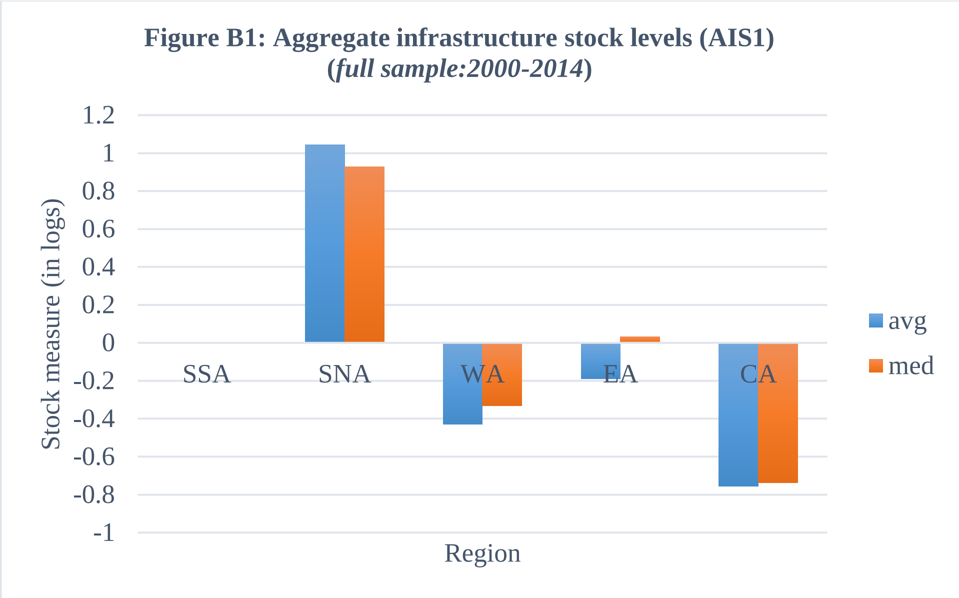
Table A2

Data information

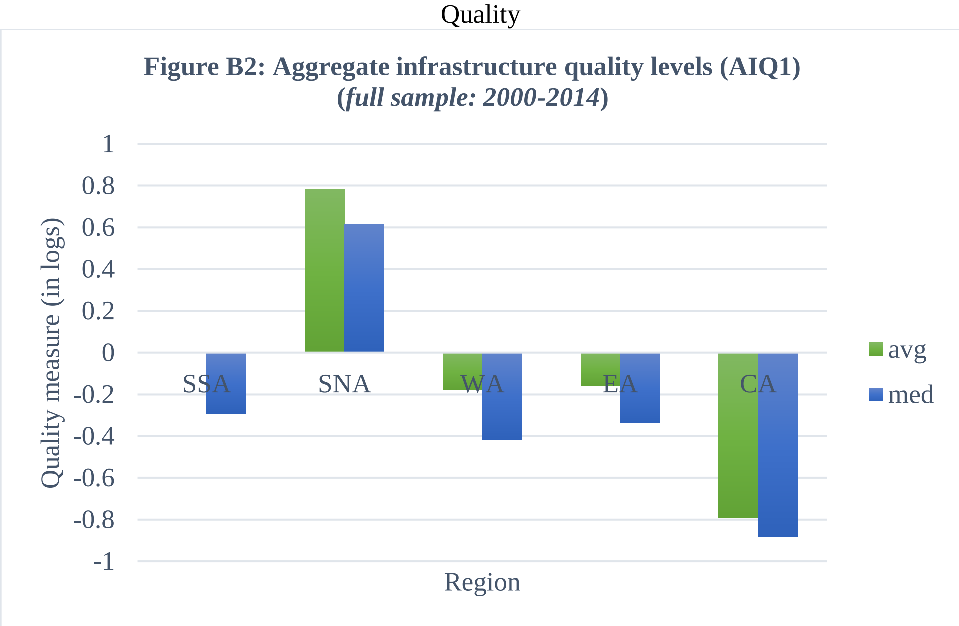
Variable	Period	Source
Infrastructure stocks:		
Net electricity generation capacity (Blns kWh)	2000-2012	Analyse Africa - below is the primary source: US Energy Information: International Energy Statistics
Telephones (subscriptions per 100 persons)	2000-2014	Analyse Africa; World Bank Group: WDI
Mobile (subscription per 100 persons)	2000-2014	Analyse Africa; World Bank Group: WDI
Roadways (km)	2000-2014	CIA Factbooks; Photius Coutsoukis
Improved drinking water (population with access)	2000-2014	WHO/UNICEF: Joint Monitoring Programme
Sanitation (population with access)	2000-2014	WHO/UNICEF: Joint Monitoring Programme
Infrastructure quality:		
Electricity distribution losses (Blns kWh)	2000-2012	Analyse Africa - below is the primary source: US Energy Information: International Energy Statistics
Mobile quality scores (score/100)	2000-2014	Mo Ibrahim Foundation: Ibrahim Index of African Governance
Paved roads (km)	2000-2013	CIA Factbooks; Photius Coutsoukis
% of population with access to drinking water (changes in relative %)	2000-2014	WHO/UNICEF: Joint Monitoring Programme
% of population with access to sanitation (changes in relative %)	2000-2014	WHO/UNICEF: Joint Monitoring Programme
GDP per capita ($US)	2000-2014	Africa Analysis - *primary source:* IMF
Inflation (Consumer prices: Annual Percentage)	2000-2014	World Bank Group: World Development Indicators
Terms of Trade	2000-2013	World Bank Group: World Development Indicators
Human Development (based on welfare provision, education & health)	2000-2014	Mo Ibrahim Foundation: Ibrahim Index of African Governance
Trade (% of GDP) = X + M share of GDP (proxy for trade openness)	2000-2014	Analyse Africa- *primary source:* World Bank Group: WDI
Domestic Credit to Private sector (% of GDP) (proxy for financial depth)	2000-2014	World Bank Group: World Development Indicators
Land Area (Square km)	2000-2014	Photius Coutsoukis
Population (millions of persons)	2000-2014	Africa Analysis - *primary source:* World Bank Group: WDI
Institutional Quality Measures on the following:		
Political stability & absence of violence/terrorism (scale: -2.5 - 2.5)	2000-2014	Analyse Africa - *primary source*: Mo Ibrahim Foundation: Ibrahim Index of African Governance
Governance (scale: 0-100)	2000-2014	Analyse Africa - *primary source*: Mo Ibrahim Foundation: Ibrahim Index of African Governance
Personal Safety (0-100)	2000-2014	Analyse Africa - *primary source*: Mo Ibrahim Foundation: Ibrahim Index of African Governance
Freedom (rating: 1-7) (1-2.5 free, 3-5 partly free, 5.5-7 free)	2000-2014	Analyse Africa - below is the primary source: Freedom House: Freedom in the World
Sub-regional categories:	*List of countries*	
Southern Africa	Angola, Botswana, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Namibia, Seychelles, South Africa, Swaziland, Zambia, Zimbabwe	
West Africa	Benin, Burkina Faso, Cape Verde, Cote d'Ivoire, Gambia, Ghana, Guinea, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone, Togo	
Central Africa	Cameron, Chad, Central Africa Republic, Congo Republic, Democratic Republic of Congo, Equatorial Guinea, Ethiopia, Gabon	
East Africa	Burundi, Comoros, Eritrea, Kenya, Rwanda, Sao Tome Principe, Tanzania, Uganda	

Appendix B: Aggregate Infrastructure

Stock



Quality



Note: SSA, SNA, WA, EA & CA stands for Sub Saharan Africa, Southern Africa, West Africa, East Africa, and Central Africa, respectively. ‘avg’ means average and ‘med’ means median. SNA has relatively better aggregate infrastructure stock and quality levels while CA has the poorest.

Sub-regional & Periodical Stocks

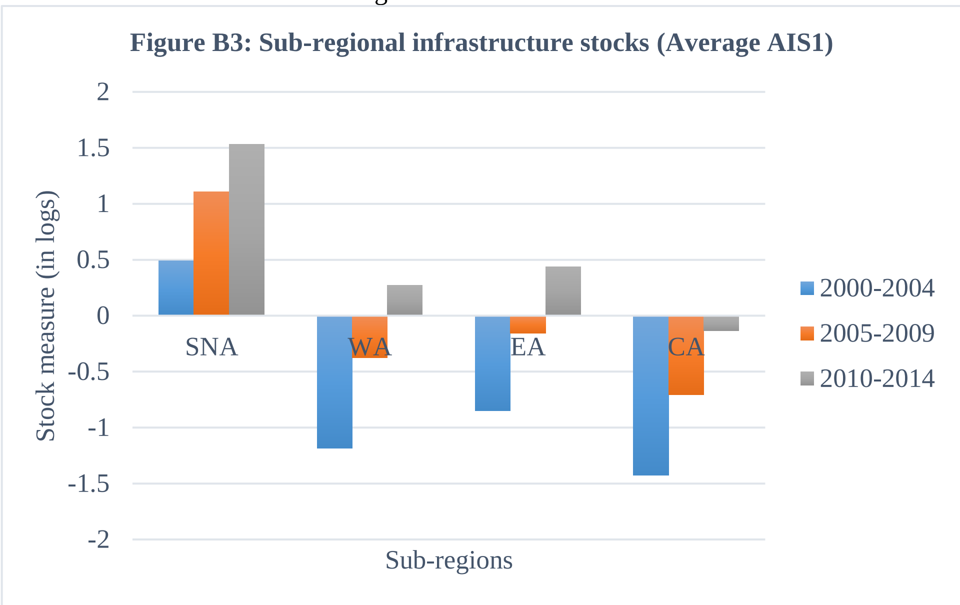


Figure B3: Sub-regional infrastructure stocks (Average AIS1)

Sub-regional & Periodical Quality

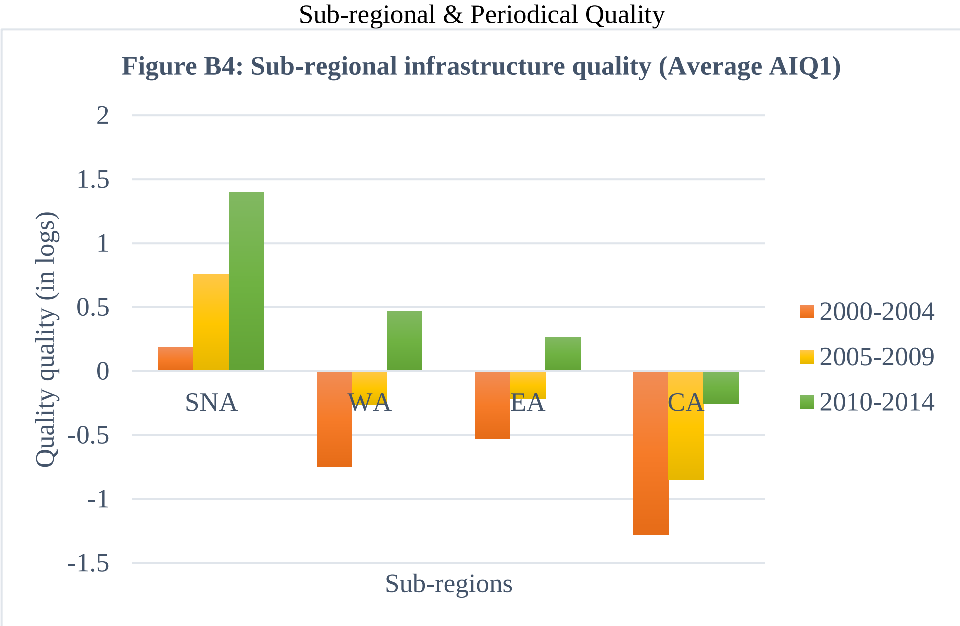


Figure B4: Sub-regional infrastructure quality (Average AIQ1)

Note: SNA performs relatively better while CA shows the poorest levels of both aggregate aggregate stock and quality in all phases.