Impact of Development Budget Deficit on Gross County Product of Counties in Kenya

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Abstract: **Globally, the performance of any economy is guided by the proportion of productive resources dedicated towards supporting its needs. Whenever their availability is low and cannot support adequately the economic needs, contribute to economic instability and this an issue of concern for many countries. Kenya established county governments in 2013 and since then, worrying trends in growth of development budget deficit (DBD) and Gross County Product (GCP) have been registered. Between 2013 and 2017 the average development budget deficit increased from 1036.19 million shillings to 1467.94 million shillings, while the average Gross County Product increased from 90.721 billion shillings to 163.259 billion shillings. However, some county governments have not realized the increase in their GCP as much, which becomes a worrying trend. Literature has given great focus on the aggregate budget deficit, while majorly considering data at the national level. The available studies also show no consensus whether these deficits have negative, positive or neutral effect on growth of an economy. The purpose of this study was to establish the impact of development budget deficit on Gross County Product of counties in Kenya. The study used panel data from 2013 to 2017 for all the 47 counties in Kenya, sourced from Kenya National Bureau of Statistics and Controller of Budget reports. A correlational research design was used, with the study modelled on Solow Swan's neoclassical economic growth theory. The panel estimation method of Random Effects as preferred by the Hausman test was used to estimate and interpret results of autoregressive distributed lag (ARDL) model. The results showed that development budget deficit had a coefficient of 0.21 with p-value of 0.056 while the coefficient of its lagged value was 0.06 with a p-value of 0.001. This implied that development budget deficit of the past had a positive impact on Gross County Product. Based on these findings, the study concluded that past increase in development budget deficit increases growth of Gross County. Based on these findings, the study recommended for spending this deficit on projects that help create capital stock, caution when spending these deficits in a way that can spur growth even in the current year, and finally for policies that helps in higher absorption rate of development budget allocations.**

Keywords: **Development budget deficit, Gross County Product, Neoclassical theory, ARDL, Counties.**

I. INTRODUCTION

Globally, the performance of any economy is dependent on productive resources available to support its needs. As the needs of a given economy usually grow, the available resources dedicated towards such needs are always insufficient. According to Osoro, (2016), the mismatch between resource base and needs of an economy is a driver of economic instability, which is a major issue of concern today for many countries in the world. At the same time, authors such as Fischer (1993), Ramu, *et.al* (2016) and Eminer, (2015) argue that budget deficit is one of the most important variables that influence economic growth. In Kenya, county governments were established in 2013 and since then, each contributes to the country's Gross Domestic Product (GDP), as measured by Gross County Product (GCP). Kenya National Bureau of Statistics (KNBS, 2019), noted that GCP may be interpreted as the "County GDP", since it measurers how much each county contributes to Kenya's GDP. Development budget deficit stems from the inability by a government to collect enough taxes to support its developmental needs, increased development spending by the government or both. As a developing country, the counties, by extension, have been focusing on large infrastructure projects, which require huge budgetary support. This is however, in contrast to low revenue generated to achieve their economic goals. According to Brender (2008), developing countries prefer expansionary fiscal policies, while developed nations prefer low inflation. As developing countries go for expansionary fiscal policies, Gupta, *et. al*. (2005) observe that higher government spending or budget deficit does not always have a negative impact on the economy. They state that even if spending is too high, but is utilized for capital (development) expenditure, then such deficit spending will contribute positively to GDP growth. This was also supported by Ramu, *et al* (2016) who found that development budget deficit had a positive relationship with GDP in India.

II. THEORETICAL FRAMEWORK

2.1 Solow-Swan's Neoclassical Economic Growth Theory

The study was modelled on the neoclassical economic growth theory, mainly the model developed by Solow-Swan. Pietak, (2014) and Aghion and Howitt, (2009) argue that any study of economic growth starts with the neoclassical growth model developed by Solow and Swan (1956). Lubega, (2017), state that the model was an extension of Harrod-Domar model, which considered a production function with capital and labour as determining output level. A third factor, technology, which in theory is determined exogenously, was added to the production function. Solow-Swan, in their model allowed for the substitution between capital and labour. Separately, capital and labour exhibit diminishing returns to scale, while jointly exhibit constant returns to scale. The progress in technology was a residual factor which explains the long run growth.

The model assumed the standard Cobb Douglas aggregate production function, represented as follows:

$$Y\ (t) = AK\ (t)^{\propto} L\ (t)^{1-\propto}, 0 < \propto < 1 \quad (1.1)$$

Where Y is the output, K is the capital stock, L is the labor force, A is the technical factor productivity whose level was assumed to be exogenously determined and $\propto$ is the elasticity of output with respect to capital. Any improvement in technology shifts the production function higher. As growth in labor (population) and labor productivity (AL) was assumed to grow independently at a constant rate, then

$$\frac{\dot{L}}{L} = n \quad (1.2)$$

This represents the compound growth rate of labor from the time (0) to time (t), which represents the stock of capital. This means that the capital stock is an important contributor to the output growth. Whereas not all output was consumed, means a fraction was saved, as capital. If its assumed that "c" is the fraction of output (cY) consumed and "s" is the fraction of output (sY) saved, as capital with "δ" as a constant rate of depreciation of this capital stock (δK), then

$$K_t = sY_t - \delta K_t, \text{ where } K_t = \frac{\delta K_t}{\delta_t} \quad (1.3)$$

Where sY_t is the aggregate saving and δK_t is the aggregate depreciation of capital over time (t). The output that was neither used for consumption nor replaced the depreciated old capital goods is the net investment. Because the production function in Solow-Swan's model exhibit constant returns to scale, it can be specified as output per unit labor in the long run analysis, as given below;

$$Y_t = \frac{K_t{}^{\propto} A_t\, L_t{}^{1-\propto}}{A_t\, L_t{}^{1-\propto}}$$

Thus $Y_t = K^{\propto}{}_t$ (1.4)

Considering our economic theory, net investment (capital accumulation) promotes economic growth. Since development budget of the government supports investment, development budget deficits will affect economic growth. Integrating the development budget deficit in the model, becomes

$$Y_t = \mathrm{f}(\phi^{\beta}{}_t) \quad (1.5)$$

Where Y is the output and ϕ is the development budget deficit.

Because the study considered panel data set with development budget deficit and other control variables, model (1.5) was expanded to capture all these variables, as specified below;

$$Y_{it} = AK_{it}{}^{\alpha}\, L_{it}{}^{\psi} DBD_{it}{}^{\beta}\, LRD_{it}{}^{\eta}\, RBD_{it}{}^{\rho} \quad (1.6)$$

Where,

Y_{it} is the Gross County Product (GCP)

A is the factor productivity which was assumed to be positively related with growth

K_{it} is the development expenditure which was assumed to be positively related with growth

L_{it} is the population (county labor force) also having a positive relationship with growth

DBD_{it} is the development budget deficit, assumed to be positively related with growth

LRD_{it} is the local revenue deficit, assumed to be negatively related with growth

RBD_{it} is the recurrent budget deficit, also assumed to be negatively related with growth

Model (1.6) was then transformed into the logarithm form, as specified below;

$$lnY_{it} = A_0 + \alpha lnK_{it} + \psi lnL_{it} + \beta lnDBD_{it} + \eta lnLRD_{it} + \rho lnRBD_{it} \quad (1.7)$$

Model (1.7) was then used to establish the impact of development budget deficit on Gross County Product of Counties in Kenya.

III. RESEARCH METHODOLOGY

3.1. Introduction

This section highlighted the research philosophy, research design, study area, target population, sampling, data collection, model specification, measurement of variables, data analysis techniques and data presentation.

3.2 Philosophy of the Study

The study was based on positivism paradigm since it depended on quantitative data. It believed that the information generated through the observations from the study variables was true. As such, the findings were guided by the available data and the objective interpretation of the study findings. Crowther, D. and Lancaster, G. (2008), observed that a general rule for the positivist paradigms, is that they are usually grounded on deductive approach. This research followed a deductive approach in interpreting its findings.

3.3 Research Design

Creswell (2008) defines a research design as the plan and procedures for a research process. It spans the decisions from broad assumptions to detailed methods of data collection and analysis, which generate answers to research problems. Kothari, (2004) also defines a research design as the arrangement of conditions for collection and analysis of data in a manner that combine research purpose with procedure. This study adopted a correlation research design. According to Simon, *et.al* (2011), correlational research design is used to establish relationships between variables. If such a relationship exists, correlation is used to determine a regression model which makes predictions to a population. This study used the Random Effects model to determine the impact of development budget deficit on Gross County Product of counties in Kenya.

3.4. Study Area

The study was conducted in Kenya, considering all the 47 counties, as per the 2010 constitution. Kenya covers an area of 582,650 sq. km, is located in Eastern Africa with latitude of 1°00'N and a longitude of 38°00'E. After the oil crisis in 1970, the country has been facing budget deficits and dwindling rates of economic growth. In 2013, Kenya established 47 county governments. Between 2013 to 2017, the country registered GDP growth rate of 5.9%, 5.4%, 5.7%, 5.9% and 4.9%. During the same period, budget deficit as a percentage of GDP registered an increasing trend. It was 39.8 in 2013, 44.2 in 2014, 48.8 in 2015, 53.8 in 2016 and 57.1 in 2017. The KNBS, (2019) indicated that since 2013, each county had been posting an increasing trend in their contribution to national GDP, through Gross County Product (GCP). At the same time, counties registered increasing trend of development budget deficits, COB reports, (2013-2017).

3.5 Target Population

Burns, *et. al* (2003) describe population as all the elements that meet the criteria for inclusion in a research study. The study considered all the 47 counties for a period of 5 years, from 2013 to 2017.

3.6 Sampling

Census sampling was applied where the data existing on counties GCP and development budget deficits were collected for all the 47 counties for a period of 5 years realizing 235 observations. Variables considered in the sampling were Gross County Product and development budget deficit. Control variables were population (proxy for labor force), development expenditure (proxy for capital stock), local revenue deficit and recurrent budget deficit as the population for this study.

3.7 Data Collection

Secondary panel data was collected for 47 Counties for the period 2013 to 2017. The data was sourced from Annual County Governments Budget Implementation Reports by the Controller of Budget (COB) and the Gross County Product (2019) published by Kenya National Bureau of Statistics (KNBS).

3.8 Model Specification

The study was based on Solow-Swan neoclassical economic growth model. To establish the impact of development budget deficit on Gross County Product of Counties in Kenya, the study's panel data analysis model (3.1) follows model (1.7), where GCP was the dependent variable and development budget deficit and other control variables were the independent variables while the error term took care of other components.

$$lnY_{it} = ß_0 + \beta_1 lnD_{it} + \beta_2 lnK_{it} + \beta_3 lnL_{it} + + \beta_4 lnLR_{it} + \beta_5 lnR_{it} + e_{it} \qquad (3.1)$$

Where,

Y_{it} is Gross County Product (GCP),

i = 1, 2, ... is the number of observations which were the 47 counties in Kenya

t = 1, 2, ... period of the study, which was five years from 2013 to 2017.

D_{it} is the development budget deficit (DBD)

K_{it} was capital stock, represented by development expenditure

L_{it} is the population (proxy for labor force) in a county

LR_{it} is the local revenue deficit (LRD)

R_{it} is the recurrent budget deficit (RBD)

$ß_0$ - Constant

$\beta_1, \beta_2, \beta_3\ \beta_4, \beta_5$ were the coefficients

e_{it} was the error term, assumed to be independent, normally distributed with constant variance and zero mean for all the individual observations at all the time.

3.9 Data Analysis

Use of descriptive and inferential statistics was employed. Oso and Onen (2009) underscores that such statistics provide a powerful way of drawing conclusions about relationships or differences found in research results.

3.9.1 Panel Unit Root Test

Maddala and Wu (1999) observed that it was essential to check stationarity of data to avoid spurious regression, which leads to misleading inferences and conclusions. Using panel data unit root tests was accepted as one way of increasing the power of unit root tests. In this research, Fisher type test was used. According to Baltagi, (2005), the Fisher type test does not require a balanced panel, making it advantageous over other unit root tests. Choi, (2001) stated that this test combines p-values from panel specific unit root tests and uses four methods. The study considered inverse normal Z statistic, which Choi, (2001) argued to have the best trade-off between power and size. He further observed that inverse normal can be used whether the sample size if finite or infinite and as such recommended it for applications. The null hypothesis of Fisher- type test is that all panels contain unit roots, against the alternative hypothesis that at least one panel is stationary. Under the null hypothesis, the Z test statistic has a standard normal distribution. Fisher -type test is given under equation (3.2) below.

$$Z = \frac{1}{\sqrt{N}} \sum_{n=1}^{N} \phi^{-1(pi)} \qquad (3.2)$$

Where $\phi^{-1}(pi)$ is the inverse of the standard normal distribution.

3.9.2 Correlation Analysis

According to Oso and Onen (2009) correlation is used in a research process to establish the magnitude and direction of association between two or more variables. The analysis was based on the null hypothesis of no relationship between county budget deficits and Gross County Product in Kenya.

3.10 Panel Analysis

Baltagi (2005) and Maddala, (1987) argues that panel data approach provides efficient and unbiased estimators. In addition, it provides a larger number of degrees of freedom, which allow researchers to overcome problems with small samples. These problems are associated with the estimation of the linear regression model, especially due to the time-dimension of the data. Spilioti (2015) added that panel data models allow researchers to analyse several important economic questions that cannot be addressed using sets of cross-sectional or time-series data alone. Arjomand, *et.al* (2016) also noted that panel data method was characterized by high capability in identifying and measuring the effects which are not easily predicted in cross-section and particular time series studies. The study applied panel data analysis using Random Effects method, as supported by the Hausman test results.

3.11 Diagnostic Tests

In this research, diagnostic tests were conducted to determine if study variables satisfied the assumptions of the regression analysis. These tests determined the distribution of random variable, relationship between error terms, the relationship between explanatory variables themselves and the constant variance of the residuals. Specific tests included the Hausman test, multicollinearity test, autocorrelation test, heteroscedasticity test and normality test. Each of these tests were highlighted below.

3.11.1 Hausman Specification Test

This study utilized test developed by Hausman (1978) to select between Fixed Effects model and Random Effects model. According to Hausman (1978), the Fixed Effects model controls for all time-invariant differences between the variables. As such the estimated coefficient of the Fixed Effects models cannot be biased because of invariant characteristic. Random Effects give better p-value, since they are more efficient. The Hausman test, was therefore useful in identifying the most efficient estimator that give consistent results. In the Hausman test, the null hypothesis suggests that Random Effects model should be preferred, with the alternative hypothesis preferring Fixed Effects model.

Table 3.1: Hausman Specification Test Results

---- Coefficients ----				
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B)
	Fixed Effect	Random Effect	Difference	S.E
lnGCP_L1	0.0155752	0.0828113	0.0983865	0.020918
lnDBD	0.0541718	0.2143817	0.1602099	0.0628195
lnDBD_L1	0.0896839	0.0623029	0.0273811	0.1517045
lnGDE	0.9572931	0.8019373	0.1553558	0.1453393
lnGDE_L4	1.763347	1.374379	-0.388968	0.1401861
lnPOP	0.0129376	0.0055082	0.0074295	0.0034366
lnPOP_L2	0.0043551	0.0001515	0.0045067	0.0032946
lnLRD	-0.0573946	-0.4453892	-0.3879946	0.2254501
lnLRD_L1	-1.101585	-1.026672	-0.0749133	0.1897163
lnRBD	-1.012593	-0.1296037	-1.142197	.
lnRBD_L4	-0.3754145	-0.0682958	-0.4437103	0.122332
b = consistent under Ho and Ha; obtained from xtreg				
B = inconsistent under Ha, efficient under Ho; obtained from xtreg				
Test: Ho: difference in coefficients not systematic				
chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 5.20 Prob>chi2 = 0.9209				
(V_b-V_B is not positive definite)				

The Hausman test results, shown in Table 3.1, reported chi square statistic of 5.20 at 9 degrees of freedom, with a p-value of 0.9209. The null hypothesis was that Random Effect model was the most preferred, against the alternative hypothesis which prefers Fixed Effect model. The reported p-value (0.9209) being greater than 0.05 means that the null hypothesis could not be rejected at 5 percent level of significance. The Random Effect model was therefore preferred.

3.11.2 Multicollinearity Test

Gujarati, (2004) state that multicollinearity arises when there is a perfect linear relationship among some or all of the independent variables in a regression model. Multicollinearity makes it difficult to determine the effect of individual regressors on the dependent variable. In this research, the Variance Inflation Factor (VIF) was used to detect multicollinearity. The null hypothesis was no multicollinearity, against the alternative hypothesis of multicollinearity.

According to Gujarati (2004), when VIF exceeds 10, as a rule of thumb, such a variable is said to be highly collinear. The VIF in this research was given by

$$VIF = \frac{1}{1 - r^2 \mathrm{x}_{it}} \qquad (3.3)$$

Where $r^2 \mathrm{x}_{it}$ was the coefficient of correlation between explanatory variables, Xi.

Table 3.2: Variance Inflation Factors Results

Variable	VIF	1/VIF
lnGCP_L1	1.86	0.537607
lnDBD	1.20	0.834484
lnDBD_L1	1.23	0.813970
lnGDE	1.07	0.932819
lnGDE_L4	1.03	0.969858
lnPOP	1.41	0.711612
lnPOP_L2	1.14	0.879055
lnLRD	2.61	0.382479
lnLRD_L1	2.02	0.494628
lnRBD	2.17	0.460581
lnRBD_L4	1.04	0.959552
Mean VIF	1.53	

The VIF test results for the regression variables were displayed in Table 3.2. These results show a mean VIF of 1.53, which was far below 10, hence the null hypothesis of no multicollinearity could not be rejected. As such, the regression variables did not suffer from multicollinearity.

3.11.3 Autocorrelation Test

Kurt, *et.al* (2012) appreciates that autocorrelation (serial correlations) is a major problem, in both time series and panel data analysis. According to him, one of the basic assumptions of regression analysis is that the error terms for different observations are not correlated. However, autocorrelation or serial correlation exists if error terms are associated with each other. Wooldridge test for autocorrelation in panel data was used in this study. The null hypothesis of this test assumes absence of autocorrelation, while the alternative hypothesis assumes presence of autocorrelation of panel data.

Table 3.3.: Wooldridge Test for Autocorrelation in Panel Data

H0: no first order autocorrelation	
F (1, 45) = 0.511	Prob > F = 0.4784

Results in Table 3.3 reported F statistic of 0.511, with a probability value of 0.4784. Since this probability was greater than 0.05, the null hypothesis of no first order autocorrelation could not be rejected at 5% level of significance. This was an indication that residuals did not suffer from first order autocorrelation.

3.11.4 Heteroscedasticity Test

Kurt, *et.al* (2012) states that in panel data analysis, homoscedasticity is one of the basic assumptions that must be tested. Breusch-Pagan test for heteroscedasticity was employed, as it is one of the most popular tests for heteroscedasticity. The null hypothesis of this test is that residuals are homoscedastic, against the alternative hypothesis that residuals are heteroscedastic.

Table 3.4: Breusch-Pagan / Cook-Weisberg test for Heteroskedasticity

Ho: Constant variance	
Variables: Residuals	
chi2(1) = 0.73	Prob > chi2 = 0.3918

The test results in Table 3.4 indicated a chi square test statistic of 0.73 at one degree of freedom, with a probability value of 0.3918. The probability value being greater than 0.05, meant that at 5% level of significance, the null hypothesis could not be rejected. The findings proved absence of heteroscedasticity among residuals.

3.11.5 Residual Normality Test

The study used Shapiro-Wilk test for testing normality of the error term. Razali and Wah, (2011), argue that among all the tests for normality, the Shapiro-Wilk test has the highest power. The null hypothesis of this test is that residuals are normally distributed. This is important, as error term is usually assumed to be normally distributed.

Table 3.5: Results for Shapiro Wilk test for Normality

Variable	Obs	W	V	z	Prob>z
Residuals	231	0.98495	2.547	2.167	0.15103

The results in Table 3.5 with a probability value of 0.15103 > 0.05 implied that the null hypothesis of residuals being normally distributed could not be rejected at 5% level of significance. This implied that residuals were normally distributed.

IV. RESULTS AND DISCUSSIONS

4.1. Introduction

This chapter presents and discusses analysis of results which covers a summary of descriptive statistics, correlation analysis, panel unit root test and panel analysis of Random Effects model and Fixed Effects model as presented in sections 4.2 to 4.6.

4.2. Unit Root Test Result

This empirical research began by examining the stationary properties of the data. Fisher type test for stationarity was used to conduct unit root test. The null hypothesis for this test is that all panels contain unit root, against the alternative hypothesis that at least one panel is stationary. The test uses four methods, proposed by Choi (2001), who further recommends use of inverse normal (Z) statistic. Choi (2001) argues that the Z statistic provides the best trade-off between size and power, among the other three Fisher-type test statistics. In addition, he argues that both inverse-normal and inverse-logit transformations can be used whether the sample size is finite or infinite. Under the null hypothesis, Z has a standard normal distribution and its low value means the null hypothesis is doubted. The unit root test results were displayed in Table 4.1.

Table 4.1: Panel Unit Root Test Results

Variable	Test in	Fisher ADF test Z statistic	Conclusion
lnGCP	Level	-15.8466 *** (0.0000)	I (0)
lnDBD	Level	-1.7292 *** (0.0419)	I (0)
lnGDE	Level	4.9037 (1.0000)	
	First difference	-9.0815 *** (0.0000)	I (1)
lnPOP	Level	-7.8873 *** (0.0000)	I (0)
lnLRD	Level	-13.2600 *** (0.0000)	I (0)
lnRBD	Level	-6.3523 *** (0.0000)	I (0)

Note. ADF is the Augmented Dickey Fuller, values in parentheses ( ) are p-values while *** indicate stationarity of the variables at 5% level of significance respectively.

The test results in Table 4.1 revealed that Gross County Product, development budget deficit, population, local revenue deficit and recurrent budget deficit were all stationary at level, an indication of integration of order zero. This was expected and may be a pointer to the effectiveness of policies put in place by the various County governments. Development expenditure was stationary after first differencing, an indication that the variable was integrated of order one. The existence of unit root in this variable was expected since development expenditure always grow and therefore has trend.

These results supported the choice of autoregressive distributed lag (ARDL) model, developed by Pesaran *et. al.* (1999), as an estimation method for this study. Cinar, *et.al* (2014) argue that ARDL model is useful when series have different cointegration levels, mainly I (0) and I (1), but not I (2). According to Olubiyi, *et.al* (2018), ARDL is a standard least squares regression, which include lags of both the dependent variable and explanatory variables as regressors. Cinar, *et.al* (2014), argue that ARDL involves the use of a single-equation set-up, is simple to implement and interpret, making it better than the cointegration analyses developed by Engle and Granger (1988) and Johansen (1995). Pesaran, *et al*. (1999), also note that ARDL is a reliable model in both big and small samples.

4.3. Lag Determination

The study ran separate regressions and used Akaike Information Criterion (AIC) to select lag length for each study variable. According to Raza, *et al.* (2015) this is the commonly used information criterion in panel estimation. The results are presented in Table 4.2

Table 4.2: Lags Selected for Study Variables

Name of Variable	Selected Lags	AIC
lnGCP	1	1.322257
lnDBD	1	0.599372
lnGDE	4	-2.539842
lnPOP	2	5.279382
lnLRD	1	-1.769081
lnRBD	4	-1.667454

4.4. Autoregressive Distributed Lag Model

4.4.1. ARDL Random Effects Model Results

The results for Radom Effects Model are displayed in Table 4.3. These results are discussed under 4.4.2.

Table 4.3: ARDL Random Effect GLS Regression Results

Random effects GLS regression Number of obs = 231
Group variable: ID Number of groups = 47
R-sq: within = 0.0731 Obs per group: min = 1
between = 0.8716 avg = 4.9
overall = 0.7060 max = 5
Wald chi2(11) = 287.31
corr(u_i, X) = 0 (assumed) Prob > chi2 = 0.0000

lnGCP	Coef.	Std. Err.	Z	P>z	[95% Conf.	Interval]
lnGCP_L1	0.0828113	0.0484657	9.43	0.000	0.361881	0.551863
lnDBD	0.2143817	0.162452	1.91	0.056	-.0076736	0.6291263
lnDBD_L1	0.0623029	0.2408685	3.38	0.001	.3417551	1.285942
lnGDE	0.8019373	.337429	4.38	0.000	0.815125	2.137822
LNGDE_L4	1.374379	0.3349669	-4.45	0.000	-2.146534	-0.8334874
lnPOP	0.0055082	.0076256	2.27	0.023	0.0023776	0.0322693
lnPOP_L2	0.0001515	.0075864	1.25	0.210	-0.0053491	0.024389
lnLRD	-0.4453892	0.6488183	-2.48	0.013	-2.882841	-0.3395206
lnLRD_L1	-1.026672	0.5369633	-2.98	0.003	-2.651212	-0.5463545
lnRBD	-0.1296037	0.3365824	-2.30	0.022	-1.433076	-0.1136969
lnRBD_L4	-0.0682958	0.5500674	-1.60	0.110	-1.958116	0.1981081
_cons	100.1561	18.86813	5.31	0.000	63.17528	137.137
sigma_ u	0.13133191					
sigma_ e	0.25204242					
Rho	0.21353637 (fraction of variance due to u_i)					

Note: Values in parentheses ( ) are p-values while *** indicate significance of variables at 5% level of significance.

4.4.2. Impact of Development Budget Deficit on Gross County Product

The objective of the study was to establish the impact of development budget deficit on Gross County Product of counties in Kenya. This was based on the null hypothesis that there was no impact of development budget deficit on Gross County Product of counties in Kenya. The Random Effect results in Table 4.3 reveal that development budget deficit had a positive coefficient (0.21) and a probability value (0.056).

Lagged development budget deficit had a positive coefficient (0.06), with a probability value (0.001). The significant positive impact means that past growth of development budget deficit increases growth of Gross County Product in the current year, such that when development budget deficit in the past increases by 1% growth of Gross County Product in the current year increases by 0.06%. The positive impact conforms to the economic a priori expectation, since past deficit spending in development projects helps in creating capital stock, which is vital for driving future economic growth. The findings were consistent with those by Ramu, *et.al* (2016) who found a statistically significant positive relationship in India.

V. SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

The objective of this study was to establish the impact of development budget deficit on Gross County Product of counties in Kenya. Results showed that growth of development budget deficit in the past had a positive impact on Gross County Product of counties in Kenya.

5.2 Conclusion

With these findings, the study concluded that an increase in development budget deficit in the past was beneficial to the future growth of counties in Kenya.

5.3 Recommendations

Given this conclusion, the following policy recommendations were proposed. First, the counties should spend their deficits on development projects that helps in creating capital stock, which is vital for driving future economic growth. Secondly counties should be cautious when spending these deficits in a way that can spur growth in the same year. Thirdly, counties to enact policies that aid higher absorption rate of their development budget allocations to spur growth.

5.4 Limitations of the Study

The study covered a shorter time span of five years, as data was available from 2013 when counties came to existence in Kenya.

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