Foreign Direct Investment and Economic Growth in Zambia

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Abstract
This paper aims to examine the causality relationship between foreign direct investment inflow (FDI) and economic growth (GDPGR) in Zambia using the time-series analyses. All analyses are conducted with the annual data of foreign direct investment and real gross domestic product of Zambia over the years of 1970 and 2011. The results of the ADF unit root test show that the time-series data are non-stationary at levels, but become stationary in the first differences. Besides, the results of the Johansen co-integration test indicate that both series are co-integrated, and long-run equilibrium thus exists between FDI and GDPGR. Findings of Granger-causality test suggest that there is a one-way causality effect running from FDI to GDPGR.

Keywords: economic growth, foreign direct investment, the ADF Unit Root test, the Johansen co-integration test, the Granger causality test, Zambia

1. Introduction
Does foreign direct investment inflow (FDI) contribute to economic growth (GDPGR) of Zambia? Most empirical studies on different countries and regions have found that FDI has economically and statistically positive effect on GDPGR. So, the Zambian government will be eager to bring more FDI into its own land and take benefit from it only if the impact of FDI on GDPGR is positive and significant. Beyond the argument from existing literature, statistical indicators show that the values of FDI in Zambia were $0.09 billion in 1970 and $1.9 billion in 2011, and the values of real gross domestic product (GDP) of Zambia were $1.7 billion and $19 billion at the same years, respectively (The value of real GDP is commonly used as proxy for economic growth). The huge and simultaneous increases in both variables imply that there should be an existence of linkage between FDI and GDPGR in Zambia according to “World Development Indicators” by the World Bank (2013).

This study makes an empirical contribution into the economic growth literature by examining the causality relationship between FDI and GDPGR in Zambia, as none of the previous works has solely focused on a case study of Zambia. In this study, I apply econometrics in time-series methods; the Augmented Dickey-Fuller (ADF) unit root test, the Johansen co-integration test, vector error correction model (VECM), and the Granger causality test. I employ them to investigate whether or not the linkage between FDI and GDPGR exists over the period of 1970 and 2011.

I organize the shape of this paper as follows: the second section brings literature review up, the third section reveals the theoretical arguments, the forth section provides detail information about the data and methodology, the fifth section shows the empirical results, and the last section summarizes the findings of this study.

2. Literature Review
Although a number of studies have shown the presence of the relationship between FDI and GDPGR, several papers have not found any connection between them. For example, Blomstrom et al. (1992) categorized 78 developing countries as low-income and high-income countries, and argued that there was no linkage between FDI and GDPGR in the low-income countries, despite that FDI positively impacted the growth in the high-income countries. Carkovic and Levine (2002) did not find a significant effect of FDI on GDPGR if the home and foreign countries were at different levels of trade-openness. Tekin (2012) did not observe a causality connection between the variables in a study of the least developed countries including Zambia using co-integration and causality techniques. Umeora (2013) revealed that FDI did not have any effect on GDPGR in a case study of Nigeria for the period 1986 through 2011.
On the other hand, one of the earlier works by Wallis (1968) noted that an increase in FDI from the USA to the European Union stimulated the economic growth of EU. In addition to that work, some empirical studies that support the FDI-GDPGR nexus, are follows: Guidotti and De Gregorio (1992) exposed that FDI was significantly and positively effective on GDPGR in a panel study of 12 Latin American countries using the annually data at the industry level for US firms during the early 1970s. Mello (1999) found a positive relationship between the variables in the long run applying the panel data methods. Zhang (1999a) found a strong Granger-causal relationship between FDI and GDPGR in five countries in the long-run and one country in the short-run by observing ten East Asian countries on a country-by-country basis. Zhang (1999b) revealed a bi-directional linkage between FDI and GDPGR in China employing a co-integration test and VECM. Ericsson and Irandoust (2001) employed the Granger causality test and revealed a one-way causality running from FDI to GDPGR in many of the observed countries over the period of 1970 and 1997. Basu et al. (2003) applied a co-integration technique and the Granger causality test on 23 developing countries for the years of 1978 and 1996 and exerted a bi-directional causality between the variables. Chowdhury and Mavrotas (2005) studied on a cross-country case between 1969 and 2000 using a co-integration method and a causality test, and concluded a bi-directional causality in Malaysia and Thailand, and one-way causality from GDPGR to FDI in Chili. Ericsson and Irandoust (2005), and Ndambendia and Njoupouognigni (2010) exhibited that FDI positively impacted GDPGR in the five Sub-Saharan African countries including Zambia by using the panel data techniques. Li and Liu (2005) revealed that FDI positively affected GDPGR based on a panel data of 84 countries over the period 1970 through 1999. Ahmed et al. (2007) investigated the causality linkage between the variables in the five Sub-Saharan African countries including Zambia, and exerted a unidirectional causality running from FDI to GDPGR. Bhattachar and Ghatak (2010) found FDI to have a positive impact on GDPGR in a study of 30 OECD countries. Yilmaz et al. (2011) and Dogan (2013) applied the time-series analyses to examine the causality interrelation between FDI and GDPGR in Turkey and showed that both series had a positive long-run relationship. Antwi et al. (2013) found that FDI contributed to economic growth in Ghana over the period 1980 through 2010.

3. Theoretical Arguments
An increase in the amount of FDI can help countries to reach a higher GDPGR. There are several channels through which FDI can foster GDPGR. First, when a multinational firm from a country decides to expand its business over borders, it must either establish a new plant or acquisition and merger in another country. For either project, the multinational firm will intuitively transfer its available advanced technology and facilities, and capital accumulation to the host country. By referring to this action by the firm, United Nations Conference on Trade and Development (UNCTAD) (1999) reported that FDI stimulated the growth through an increase in the efficiency of total investment. Wang (2009) noted that FDI promoted host countries’ GDPGR because of the fact that capital movement and improvement in technology were the mainstreams for the economies. Bhattacharai and Ghatak (2010) report that an action of importing the high level of technology, and production process stimulate the efficiency in production and distribution levels, and the amount of domestic capital stock in the home country, and this action also increases the level of living standards and welfares in both the home and the foreign country.

Second, neither several governments nor local firms of the least developed countries are able to make costly investments, to make expenditure on R&D, and to extract worthy natural resources because of the high fixed cost. Yilmazer (2010) indicated that FDI stimulated GDPGR through increases in the infrastructure investments, in the level of technology, and in the used amount of resources.

A couple of studies have explored how much the governments are willing to have more FDI. For example, Aitken and Harrison (1999) argued that many countries simplified their regulations on FDI, and offered serious tax reductions and subsidies to bring more FDI into their own lands. Ford et al. (2008) exerted that many governments had public departments which used dedicated public funds to pull FDI towards their own home.

4. Data and Methodology
The data used in this study are:
1) Annual percentage growth rate of GDP (as proxy for economic growth) at market prices based on the constant local currency.
2) Total net inflows of foreign direct investment (FDI) as a percentage of GDP over the period of 1970–2011.

The data on FDI and GDPGR are drawn from the World Bank’s “World Development Indicators”. Aggregates are based on 2005 U.S. dollars, and converted from domestic currencies by using the annual exchange rates by the World Bank.
4.1 Model Specification

The relationship between foreign direct investment inflow and economic growth in Zambia is stated as:

\[ FDI_t = \pi_0 + \pi_1 \times GDPGR_t + \zeta_t \]

and

\[ GDPGR_t = m_0 + m_1 \times FDI_t + \eta_t \]

where the parameter \( \zeta \) and \( \eta \) are normally distributed error terms.

5. Empirical Results

5.1 Unit Root

The main purpose of applying a unit root test is empirically observing whether or not a time-series variable is stationary. The variable will be said to be stationary if and only if it does not contain a unit root. Granger and Newbold (1974) stated that the regression was likely to be spurious which had high \( R^2 \) (goodness of fit), and statistically significant coefficients and the results were without any economic meaning when the variables were non-stationary.

I apply one of the most popular methods, the ADF unit root test, to conclude whether or not both series are stationary. ADF unit root test was first introduced by Dickey and Fuller in 1979, and takes the following form (1):

\[ \Delta X_t = \alpha + \beta X_{t-i} + \sum_{i=1}^{k} \lambda_i \Delta X_t - i + \gamma T + \varepsilon_t \]  

where \( \varepsilon_t \) is a normally distributed white noise error term, \( T \) is a deterministic time trend, \( X_{t-1} \) is the lagged values of the variable, \( \Delta X_{t-i} \) are the lagged values of the first differences of the variable, and \( \gamma, \lambda, \beta, \alpha \) are the estimated parameters. The right lag length is determined by the method of Said and Dickey (1984), \( k = N^{1/3} \), where \( N \) is the number of observations in a time-series and \( k \) is the optimal lag length. One of the important steps is selecting 'k' along the test process because of two reasons; (1) if 'k' is too small, some serial correlation can be left in the errors and the test result will be biased, (2) if 'k' is too large, power of the test will reduce. The appropriate lag length is approximately four for each variable as both have 42 pairs of observations.

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The further step is defining correct hypothesis, and options. The null hypotheses with an option of trend in Table 1 are that FDI and GDPGR have a unit root, and the alternative hypotheses are that neither has a unit root. Both the \( z \)-scores and \( p \)-values yield that both variables have a unit root because I fail to reject the null hypotheses at 5% level of significance.

Table 1. ADF Unit Root test at levels

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Test Statistic</th>
<th>1%-Critical Value</th>
<th>5%-Critical Value</th>
<th>10%-Critical Value</th>
<th>p-value</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>FDI</td>
<td>1.01</td>
<td>-3.668</td>
<td>-2.966</td>
<td>-2.616</td>
<td>0.9944</td>
<td>Fail to Reject</td>
</tr>
<tr>
<td>GDPGR</td>
<td>-0.731</td>
<td>-3.668</td>
<td>-2.966</td>
<td>-2.616</td>
<td>0.8387</td>
<td>Fail to Reject</td>
</tr>
</tbody>
</table>

One of the common ways will be taking the first differences of the variables to make them stationary if the time-series are concluded to be non-stationary. Thus, I take the first differences of FDI and GDPGR. The null hypotheses and the alternative hypotheses without an option of trend in the table 2 are set up as that both variables have a unit root, and neither has a unit root, respectively. Because the ADF test statistic is smaller than 5% the critical value, the null hypotheses of having a unit root are rejected for both series. Therefore, the variables have become stationary and are integrated in order one, I (1).

Table 2. ADF Unit Root tests on first-differences

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Test Statistic</th>
<th>1%-Critical Value</th>
<th>5%-Critical Value</th>
<th>10%-Critical Value</th>
<th>p-value</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>FDI</td>
<td>-4.242</td>
<td>-3.675</td>
<td>-2.969</td>
<td>-2.617</td>
<td>0.0006</td>
<td>Reject</td>
</tr>
<tr>
<td>GDP</td>
<td>-4.043</td>
<td>-3.675</td>
<td>-2.969</td>
<td>-2.617</td>
<td>0.0012</td>
<td>Reject</td>
</tr>
</tbody>
</table>
Tari (2005) argued that two or more time-series data might be co-integrated if they were integrated in the same order, and stated that the variables at levels did not cause a spurious regression. Thus, the co-integration techniques are applied onto FDI and GDPGR as both of the time-series are I(1).

5.2 Co-Integration Test

Co-integration implies that one or more linear combinations of the time-series variables are stationary even though they are individually non-stationary according to Dickey et al. (1991). Granger and Newbold (1974) reported that a possible presence of co-integration had to be taken into account when one selected a method to test existence of the relationship between two non-stationary variables.

Before moving to the co-integration test, I first should determine the optimal lag length using the criteria such as AIC, BIC, and SIC. I then look at the following output in the table 3 to figure out it. Indeed, the stars show that the right lag length is three. Please note that information criteria have to be minimized, and that’s the reason why the stars are at certain values.

<table>
<thead>
<tr>
<th>Lag</th>
<th>LL</th>
<th>LR</th>
<th>df</th>
<th>p</th>
<th>FPE</th>
<th>AIC</th>
<th>HQC</th>
<th>SBIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-197.84</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>227.458</td>
<td>11.1027</td>
<td>11.1334</td>
<td>11.1907</td>
</tr>
<tr>
<td>1</td>
<td>-189.24</td>
<td>12.205</td>
<td>4</td>
<td>0.002</td>
<td>176.271</td>
<td>10.847</td>
<td>10.9391</td>
<td>11.1109</td>
</tr>
<tr>
<td>2</td>
<td>-172.27</td>
<td>33.945</td>
<td>4</td>
<td>0</td>
<td>85.9853</td>
<td>10.1263</td>
<td>10.2798</td>
<td>10.5662</td>
</tr>
<tr>
<td>3</td>
<td>-163.65</td>
<td>17.242*</td>
<td>4</td>
<td>0.002</td>
<td>66.9452*</td>
<td>9.8696*</td>
<td>10.084*</td>
<td>10.484*</td>
</tr>
<tr>
<td>4</td>
<td>160.35</td>
<td>6.6036</td>
<td>4</td>
<td>0.158</td>
<td>70.4064</td>
<td>9.9083</td>
<td>10.1847</td>
<td>10.7001</td>
</tr>
</tbody>
</table>

After selecting the right lag length, the Johansen ML co-integration test introduced by Johansen (1988; 1991) is used to conclude whether FDI and GDPGR are co-integrated. This test involves the proof of the relationship between the variables and takes the following vector auto-regression (VAR) model (2):

\[ \Delta \ln Y_t = \sum^{k}_{i=1} \Gamma_i \Delta \ln Y_{t-i} + \Pi \ln Y_{t-i} + \varepsilon_t \]  

where \( Y_t \) represents n*1 vector of I(1) variables, namely FDI and GDPGR. The parameter \( \Gamma \) and \( \Pi \) represent for n*n matrix of coefficients to be tested. All I need to know is that if the rank is zero, there will be no co-integrating relationship. If the rank (r) is one there will be one co-integrating relation, if it is two there will be two and so on. When there is a co-integration between two time-series, these series have a long-run relation and cannot go too much away from each other.

This test is based on the maximum likelihood estimation and two statistics: maximum eigenvalue (\( K_{max} \)) and a trace-statistics (\( \lambda_{trace} \)), where the \( \lambda_{trace} \) statistic tests the null hypothesis that \( r \) is equal to zero (no co-integration) against a general alternative hypothesis of \( r \geq 0 \). The \( K_{max} \) statistic tests the null hypothesis that the number of co-integrating vectors is \( r \) versus the alternative of \( r+1 \) co-integrating vectors. The result in the table 4 indicates that the null hypothesis of no co-integration is rejected for the rank of zero at 5% level of significance since trace statistic is bigger than 5% critical value. In the next step, the null hypothesis of “1 co-integrating equation” versus “2 co-integrating equations” cannot be rejected at 5% level of significance as trace statistic is smaller than 5% critical value. I finally conclude that there is one co-integrating equation that allows me to identify VECM.

<table>
<thead>
<tr>
<th>Maximum Rank</th>
<th>parms</th>
<th>LL</th>
<th>eigenvalue</th>
<th>trace statistic</th>
<th>5% critical value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>10</td>
<td>-186.64</td>
<td>16.9291</td>
<td>15.41</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>13</td>
<td>-178.19</td>
<td>0.35195</td>
<td>0.0116*</td>
<td>3.76</td>
</tr>
<tr>
<td>2</td>
<td>14</td>
<td>-178.18</td>
<td>0.0003</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

5.3 Vector Error Correction Mechanism

If two variables are co-integrated by a common factor (co-integrating vector) it will not be possible to use VAR analysis. I have to account for this relationship and use VECM which adjusts short run changes in variables and
deviations from equilibrium. I must make sure of that the estimated parameter of ‘equation one’ in VECM will be negative and statistically significant if VECM is a correct technique to follow up. The negative sign guarantees that deviations in the short-run make the long-run relationship exist.

Table 5. The result of VECM

<table>
<thead>
<tr>
<th>Co-integrating equations</th>
<th>Parms</th>
<th>chi2</th>
<th>P&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>_ce1</td>
<td>1</td>
<td>12.92023</td>
<td>0.0003</td>
</tr>
</tbody>
</table>

Johansen normalization restriction imposed

| beta | Coef. | Std. Err. | z      | P>|z|  | [95%Conf. Interval] |
|------|-------|-----------|--------|-----|------------------|
| GDPGR | 1     | .         | .      | .   | .                |
| FDI  | -0.8204 | 0.20599  | -3.59  | 0   | -1.1441          | -0.3367          |
| _cons | 0.3361 | .         | .      | .   | .                | .                |

The table 5 shows that the coefficient of ‘equation one’ is -0.82, and statistically significant at 5% level. Besides, error correction mechanism works and any short-term fluctuations between the time series of GDPGR and FDI lead to a stable long run relationship since the value of coefficient lies down between zero and minus one. Referring to Ghatak (1998), 82% of disequilibrium is “corrected” each year.

Granger (1988) imposed that if two series were co-integrated, there would be at least one Granger-causality between the variables. In the next section, I investigate the direction of the linkage between FDI and GDPGR.

5.4 Granger Causality

Granger (1988) reported that the Granger causality test was a statistical hypothesis test for determining whether one time series was useful in forecasting another. It will be relevant only if the variables are either stationary or non-stationary but co-integrated. The equations are:

\[ \ln GDPGR_t = \alpha_1 + \beta_1 \ln GDPGR_{t-1} + \beta_2 \ln GDPGR_{t-2} + \ldots + \beta L \ln GDPGR_{t-L} + \delta_{t} \]

\[ \ln FDI_t = \alpha_2 + \gamma_1 \ln FDI_{t-1} + \gamma_2 \ln FDI_{t-2} + \ldots + \gamma L \ln GDPGR_{t-L} + \lambda_{t} \]

where \( \varepsilon_t \) and \( \varepsilon_{it} \) are white noise error terms, and \( \beta, \delta, \gamma, \lambda \) are the parameters which tell reveal how well the past values of the variables explain the current value of either series. The null hypothesis in general is variable X does not Granger cause variable Y. In this study, there are two null hypotheses: FDI does not Granger cause GDP, and GDPGR does not Granger cause FDI. Please note that the null hypothesis of no Granger causality cannot be rejected if and only if no lagged value of an explanatory variable is retained in the regression (3) and or in the regression (4).

Table 6. The result of the Granger Causality test

<table>
<thead>
<tr>
<th>Granger causality Wald tests</th>
<th>Equation</th>
<th>Excluded</th>
<th>chi2</th>
<th>df</th>
<th>Prob&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>FDI</td>
<td>GDPGR</td>
<td>1.1729</td>
<td>1</td>
<td>0.279</td>
<td></td>
</tr>
<tr>
<td>FDI</td>
<td>ALL</td>
<td>1.1729</td>
<td>1</td>
<td>0.279</td>
<td></td>
</tr>
<tr>
<td>GDPGR</td>
<td>FDI</td>
<td>11.9</td>
<td>1</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>GDPGR</td>
<td>ALL</td>
<td>11.9</td>
<td>1</td>
<td>0.001</td>
<td></td>
</tr>
</tbody>
</table>

The result in the table 6 indicates that I reject the null hypothesis of the case that FDI does not Granger cause GDPGR, whereas I fail to reject the null hypothesis of the case that GDPGR does not Granger cause FDI at 5% level. Therefore, it appears that there is a one-way causality running from FDI to GDPGR.

6. Summary and Conclusions

This study aims to analyze the causality relationship between foreign direct investments inflow (FDI) and
economic growth (GDPGR) in Zambia using the annual percentage rate data on GDP and FDI over the period 1970 through 2011. The paper reveals that there is a unidirectional linkage running from FDI to GDPGR. The results of the ADF unit root test show that the variables are non-stationary at levels, but become stationary in the first differences. The result of the Johansen co-integration test exhibits that there is a long-run relationship between FDI and GDPGR, and the effect is statistically significant. The finding of Granger causality test exposes that there is a one-way causality running from FDI to GDPGR. The overall results of this paper support the FDI-GDPGR nexus as opposed to the recent case studies mentioned in the literature review. This study might have given more robust results if there was a longer time-series data available for Zambia. Yet, this paper still suggests that politics and economists of Zambian government should give more attention attracting more FDI into Zambia in order to foster GDPGR. The further study can investigate the relationship between FDI, trade openness, and GDPGR in Zambia.

References


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