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# FOREIGN AID, POVERTY AND ECONOMIC GROWTH IN DEVELOPING COUNTRIES: A DYNAMIC PANEL DATA CAUSALITY ANALYSIS

Edmore Mahembe<sup>1</sup> and Nicholas M. Odhiambo<sup>2</sup>

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## Abstract

*This article examines the causal relationship between foreign aid, poverty and economic growth in 82 developing countries for the period 1981–2013. Taking advantage of the recently developed dynamic panel data estimation techniques, the paper tests for both panel unit roots and cointegration before employing the panel vector error-correction model (VECM) Granger causality test. The main findings are that in the short run, there was evidence of (a) a bidirectional causal relationship between economic growth and poverty; (b) a unidirectional causal relationship from economic growth to foreign aid; and (c) unidirectional causality from poverty to foreign aid. In the long-run, the study found that (a) foreign aid tends to converge to its long-run equilibrium path in response to changes in economic growth and poverty; and (b) both economic growth and poverty jointly Granger cause foreign aid.*

**Keywords:** official development assistance (ODA); foreign aid; poverty; economic growth; dynamic panel data analysis; Granger Causality; vector error-correction model (VECM).

**JEL Classification:** F35; I32; C23

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## 1. Introduction

According to official data collected by The Organisation for Economic Co-operation and Development's (OECD) Development Assistance Committee (DAC), official development assistance (ODA) or foreign aid, from all donors reached a new peak of US\$176 billion (at constant prices) in 2016, up from US\$162 billion in 2015 (OECD, 2017). By 2013 it was estimated that total foreign aid since 1960 amounted to US\$4.7 trillion in 2013 prices (Ravallion, 2016, p. 518). In the 1960s, ODA used to constitute around 55 percent of all net disbursements by DAC countries but has since decreased to around 30 percent in recent years. The proportion of private flows, which include foreign direct investment (FDI) and commercial bank loans, has grown from 29 percent to 57 percent over the same period. Despite these shifts, Arvin and Lew (2015, p. 1) still believes that *“foreign aid today is one of the most important factors in international relations and in the national economy of many countries.”*

As a result of these volumes, foreign aid has attracted an unprecedented amount of attention from politicians, scholars, media and even celebrities (Easterly, 2008; Moyo, 2009). This massive amount of attention also caused huge and polarising debates on the effectiveness of foreign aid in delivering on the developmental goals (sustained economic growth and poverty reduction), with poverty reduction emerging as an explicit objective since the introduction of the Millennium Development Goals (MDGs) (Sachs, 2005; Ravallion, 2016). In actuality, the first goal of the MDG was to halve the global “US\$1 a day” poverty rate by 2015. Furthermore, one of the main targets of the recently promulgated Sustainable Development Goals (SDGs) is to eradicate extreme poverty for all people everywhere by 2030 (United Nations, 2014). To achieve this global poverty reduction goal, rich nations made further commitments to increase aid to poor countries by 0.7 percent of their gross national income (GNI), a target set during

the 1960s. The United Nations (UN) has emphasised the importance of foreign aid as “*one of the most powerful weapons in the war against poverty*” (United Nations, 2005, p. 16).

Several theories have been advanced, and a number of empirical studies carried out, on the effectiveness of foreign aid (herein referred to as aid effectiveness literature, AEL) since the early 1950s, but the debate is far from over. The majority of the studies are focused on the impact of foreign aid on economic growth, though there has been a recent surge of studies looking at the effectiveness of foreign aid on poverty reduction.

This paper adds to a small body of AEL which examines the direction of causality between foreign aid and extreme poverty in developing countries. The study uses recent dynamic panel data estimation techniques, including those methods which deal with endogeneity by controlling for simultaneity and the unobserved heterogeneity. Following Arvin and Barillas (2002), this paper examines (i) whether foreign aid inflows impact poverty, whether poverty influences foreign aid allocation, or (iii) whether causality proceeds in both directions simultaneously.

The rest of the paper is organised as follows: Section 2 presents the survey of both theoretical and empirical literature, section 3 presents the model specification and estimation methodology, section 4 discusses the data, section 5 covers the empirical results while section 6 offers concluding remarks.

## **2. Survey of the Literature**

According to Todaro and Smith (2012), until recently, it was assumed in economic development policy discussions, that an increase in economic growth would naturally “trickle down” to the general population and ultimately, result in poverty reduction (Aghion & Bolton,

1997). Though several studies have criticised the notion of direct “trickle down” economics, recent studies have confirmed that economic growth and the quality of growth are important for poverty reduction (Norton, 2002; Dollar & Kraay, 2002; Feeny, 2003).

The formalisation of foreign aid in the 1940s and the subsequent allocation criteria up to the late 1980s was informed by the thinking that boosting economic growth would automatically translate into poverty reduction. Earlier theorists argued that foreign aid provides the necessary capital to boost development countries into self-sustaining economic growth (Nurske, 1953; Lewis, 1954). The main assumption was that if aid has a positive impact on growth and if growth reduces poverty, then aid contributes to poverty reduction (Burnside & Dollar, 2000; Collier & Dollar, 2001, 2002; Guillaumont & Wagner, 2014; White, 2015).

Apart from economic growth, other channels through which foreign aid affects poverty include: (i) through its influence on the public-sector spending of the recipient government which might lead to human development and welfare indicators; (ii) stabilisation of the recipient country’s economic growth; and (iii) building of democratic and economic institutions, among others. Below, we briefly discuss previous empirical studies which examined the causal relation between foreign aid, poverty and economic growth.

## **2.1. Studies on causality between foreign aid and poverty**

Hoffman (1991) examined the causal relationship between poverty in female-headed households with small children and aid to families with dependent children (AFDC) via transfer payments using the United States of America (USA) data for the period 1959 to 1988. The study used a Granger causality test, and found weak statistical evidence that receipt of aid

'Granger causes' poverty, but found strong statistical evidence that an increase in real value of aid 'causes' a reduction in poverty.

Arvin and Barillas (2002) employ Granger causality to investigate the direction of causality between aid and poverty in a bivariate framework and then included democracy in a trivariate Granger model. Both the bivariate and trivariate models are tested on annual data from 1975 to 1998 from a sample of 118 aid-receiving countries. The study categorised countries into two broad groups: geographical regions and levels of income. For the full sample, the study results show that aid was not affecting poverty and vice versa. For the sub-samples, sub-samples aid was found to reduce poverty in East Asia Pacific region, but had a detrimental impact on poverty in low-income countries (Arvin & Barillas, 2002, p. 2154).

## **2.2. Studies on causality between foreign aid and economic growth**

A recent study by Forson *et al.* (2015) examined the causal relationship between European Union (EU) aid inflows and economic growth in Ghana during the period from 1970-2013. Granger causality was tested using the Vector Error-Correction Model (VECM), and the study found evidence of an independent short-run causal relationship between the two variables and a long-run unidirectional causal relationship from EU aid inflows to GDP growth. Amin (2017) used the same approach to conduct a Granger Causality test between economic growth, foreign aid and other variables using data for Bangladesh for the period from 1980 to 2013. The study did not find any statistical evidence for short-run causality between economic growth and foreign aid, but found evidence that in the long-run, causality was unidirectional from economic growth to foreign aid.

Tekin (2012a) investigated the causal relationship among foreign aid, trade openness and economic growth in the African least developed countries (LDC) for the period between 1970 and 2010; using the seemingly unrelated regressions (SUR) estimator proposed by Zellner (1962). The results from this study showed little evidence of any causal relationship between foreign aid and economic growth. Another study by Asteriou (2009) used the autoregressive distributed lag (ARDL) approach to investigate the long-run relationship between foreign aid and economic growth using panel data for five South Asian countries for the period 1975 to 2002. The paper found a positive long-run relationship between aid and GDP growth.

### **2.3. Studies on causality between economic growth and poverty**

Some of the earliest studies to investigate the relationship between economic growth and poverty and whether economic growth ‘trickles down’ to poverty reduction were by Thornton *et al.* (1978, 1980). Using the United States of America (USA) data for the period 1947 to 1974, the two studies found that economic growth alleviates the incidence of poverty. This finding was also supported by de Janvry and Sadoulet (2000), using a panel of 12 Latin American countries between 1970 and 1994. However, using a sample of Latin American countries, Korzeniewicz (2000) concluded that economic growth had not led to significant poverty reduction in the region.

Using the ARDL-bounds testing approach to co-integration, and the ECM-based Granger causality method, Nindi and Odhiambo (2015) examined the causal relationship between poverty reduction and economic growth in Swaziland during the period 1980–2011. The main results from the empirical investigation are that (i) economic growth does not Granger cause poverty reduction in the short run and in the long run, and (ii) property reduction Granger causes economic growth in the short-run.

A recent study by Perez-Moreno (2016) used a panel of 52 developing countries for the years from 1970 to 1998 to examine causality between economic growth (proxied by real GDP per capita) and extreme poverty (proportion of people living on less than US\$1/day). The study found that economic growth unidirectionally causes poverty reduction. Pradhan and Arvin (2015) used a panel VECM framework for the period 1961-2012 to investigate the causal relation between foreign aid and economic growth and other two variables. The panel cointegration tests found evidence of the existence of a long-run equilibrium relationship among the four variables and in the short-run, foreign aid was found to unidirectionally Granger cause economic growth. There was evidence of bidirectional causality in the long-run.

### **3. Model Specification and Econometric Methodology**

The main objective of this study is to examine the causal relationships among foreign aid, poverty and economic growth. Causality is investigated through the Granger (1969) causality framework (Green, 2003; Gujarati & Porter, 2009; Wooldridge, 2013). The main assumption in the Granger (1969) causality test literature is that a variable (say X) can only be said to cause (Granger cause) another variable (say Y) if current values of Y are conditional on past values of X. In other words, the future cannot cause (or predict) the past.

Recent developments in the Granger (1969) causality literature have seen the extension of this methodology from time series to panel data. Further developments have also included the need to test for the time series properties of the data, including stationarity and cointegration tests. If the variables are integrated of the same order  $I(1)$  and are co-integrated, Granger causality can be tested through the VECM as proposed by Granger (1988) while a vector autoregressions (VARs) approach could be employed if the variables are not co-integrated (Dumitrescu & Hurlin, 2012; Mahembe, 2014; Muye & Muye, 2016).



Furthermore, the two step Engle-Granger causality procedure, in the VECM framework, allows for testing both short- and long-run causality. There are three possible Granger (1969, 1988) causality outcomes: (i) unidirectional causality between two variables, which support a supply-leading or a demand-following hypothesis; (ii) bidirectional causality, supporting the feedback hypothesis; and (iii) independence or no causality, which supports a neutrality hypothesis. There are three types of causal inferences in this set up; namely: (i) short-run causal effects, (ii) long-run causal effects, and (iii) strong causal effects, which is a situation where there is evidence of both short- and long-run causal effects. There is also a possibility that the system can have evidence of long-run causality without short-run causality. This is, however, an exception.

### 3.1. Model specification

The model specification follows that by Holtz-Eakin *et al.* (1988), and describes the causal relationship between foreign aid, poverty and economic growth, as shown in Equation 1.

$$POV = f(ODA, GDP) \quad [1]$$

where  $POV$  is poverty headcount rate,  $ODA$  is foreign aid as a percentage of GNI and  $GDP$  represents economic growth. Following Pradhan and Arvin (2015), this structural causal framework can be written in the VECM and matrix format as shown in Equation 2.

$$\begin{bmatrix} \Delta POV_{it} \\ \Delta ODA_{it} \\ \Delta GDP_{it} \end{bmatrix} = \begin{bmatrix} \alpha_{1j} \\ \alpha_{2j} \\ \alpha_{3j} \end{bmatrix} + \sum_{k=1}^{q-1} \begin{bmatrix} \beta_{11ik}(L)\beta_{12ik}(L)\beta_{13ik}(L) \\ \beta_{21ik}(L)\beta_{22ik}(L)\beta_{23ik}(L) \\ \beta_{31ik}(L)\beta_{32ik}(L)\beta_{33ik}(L) \end{bmatrix} \begin{bmatrix} \Delta POV_{it-k} \\ \Delta ODA_{it-k} \\ \Delta GDP_{it-k} \end{bmatrix} + \begin{bmatrix} \lambda_{1j}ECT_{it-1} \\ \lambda_{2j}ECT_{it-1} \\ \lambda_{3j}ECT_{it-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \\ \varepsilon_{3it} \end{bmatrix} \quad [2]$$

where  $POV$ ,  $ODA$  and  $GDP$  are as defined in Equation 1, which alternate in taking the dependent and explanatory variable roles;  $\Delta$  is the first difference operator  $(I - L)$ ;  $i = 1, \dots$ ,

$N$ ;  $t = 1, \dots, T$ ;  $\alpha_s, \beta_s$ , and  $\lambda_s$  ( $j=1, \dots, 3$ ) are parameters to be estimated;  $\varepsilon_{jt}$  ( $j=1, \dots, 3$ ) are white noise error terms;  $ECT_{it-1}$  are the lagged values of the error correction terms from the co-integration regressions while  $\lambda_s$  are speed of adjustment along the long-run equilibrium path. Short-run causality is inferred from the lagged dynamic variables of the explanatory variables ( $\beta_s$ ) using the partial  $\chi^2$  statistics of the Wald test (Wald, 1943) while the long-run causality is tested through the lagged co-integrating vectors  $ECT_{t-j}$  ( $\lambda_s$ ).

### 3.2. Panel data unit root tests

One of the key requirements for panel VECM is that the variables' stationarity properties be tested. This is done through panel unit root tests, which examine the order of integration where the panel variable attains stationarity (Pradhan & Arvin, 2015, p. 241). There are several panel unit root tests, but the main ones from empirical literature are Levin *et al.* (2002) (LLC) and Im *et al.* (2003) (IPS). Though both tests are based on the augmented Dickey-Fuller (ADF) principle (see Equation 3 below), the main difference between the two is that the former assumes homogeneous unit root across all cross-sections while the later allow for heterogeneity (Baltagi, 2013, p. 276).

$$\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{L=1}^{Pi} \theta_{iL} \Delta y_{i,t-L} + \alpha_{mi} d_{mt} + \varepsilon_{i,t} , \quad \text{for } m = 1, 2, 3. \quad [3]$$

where  $d_{mt}$  denotes the vector of deterministic variables,  $\rho_i$  is the lag-order which is permitted to vary across cross-sections and is determined by choosing a  $\rho_{max}$  and then use a  $t$ -statistic of  $\theta_{iL}$ ;  $\varepsilon_{i,t}$  is assumed to be independently distributed across  $i$  and  $t$ ,  $i = 1, \dots, N$ ,  $t = 1, \dots, T$ .

The results of the panel unit root tests inform the panel causality tests procedure. As indicated above, two important conditions for estimation of panel VECM Granger causality test are that the variables must be stationary and integrated of order one (i.e.  $I(1)$ ).

The null hypothesis under both LLC and IPS is that the series contains a unit root against the alternative that each series is stationary. The IPS is preferred due to its ability to cater for individual country heterogeneity. The panel unit root tests are performed on each of the three variables on both level and first-differences. For a robustness check, two other tests were also conducted, namely: Fisher-ADF and Fisher-Phillips-Perron (Fisher-PP) (Madala & Wu, 1999; Choi, 2001) panel unit root tests.

### **3.3. Panel cross-sectional dependency tests and determination of optimal lags**

Testing for cross-sectional dependency (CSD) is one of the key issues to consider when dealing with panel data Granger causality tests (Muye & Muye, 2016). Due to increased globalisation and the interconnectedness of the developing countries in our sample, there is a possibility that a structural upheaval, or shock in one country could affect other countries in the sample. The null hypothesis is that there is no CSD (correlation) in residuals, and the test statistic is asymptotically distributed as standard normal (Tekin, 2012b). We use both the Breusch and Pagan (1980) and Pesaran (2004) tests, though the former is more mainly valid for large T and small N (Pesaran, 2004). The latter was mainly used for robustness checks.

Panel Granger causality tests are known to be sensitive to lag lengths and therefore it is important to establish the optimal lags (Konya, 2006; Mahembe & Odhiambo, 2016; Tekin,

2012b). The most common lag length selection methods<sup>3</sup> in literature are Akaike information criterion (AIC) (Akaike, 1974) and Schwarz information criteria (SC) (Schwarz, 1978). Other researchers compared the two models and found that both are generally valid in optimal model selection, though Kuha (2004) and Wang and Liu (2006) showed evidence that the SC performs better. Winker and Maringer (2005) showed that SC performs relatively well in the VECM framework. This study therefore used the SC, using the unrestricted VAR model, to determine the optimal lag selection. The AIC was also used for robustness checks.

### **3.4. Panel cointegration tests**

Panel cointegration tests are conducted to determine whether there is a long-run equilibrium relationship between non-stationary variables. The results of the panel cointegration tests influence the panel Granger causality test strategy and model specification (Karanfil & Li, 2015). A result which shows panel variable cointegration implies that the variables under consideration move together over time so that short-term disturbances are corrected in the long-run (Engle & Granger, 1987; Stock & Watson, 1993), and therefore causality should be investigated through the panel VECM framework. Conversely, lack of cointegration suggests that the variables do not have a long-run relation and therefore tend to move randomly away from each other (Granger, 1988), and hence a panel VAR should be estimated for causality analysis.

Just like the panel unit root tests, there are several panel cointegration tests used in empirical literature. These panel cointegration tests can be divided into two broad groups, namely those which are residual based and the likelihood-based tests. The most popular test from the first

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<sup>3</sup> Other lag length selection methods include: Sequential modified LR test statistic (LR); Final prediction error (FPE); and Hannan-Quinn information criterion (HQ).

group is the one developed by Kao (1999), while the Pedroni (1999, 2004) panel cointegration tests are a set of seven tests which combine the residual-based Lagrange multiplier (LM) tests, ADF and PP principles. This study uses both the Kao (1999) and Pedroni (1999, 2004) panel cointegration tests. The Kao (1999) test assumes homogenous or a common co-integrating vector while the Pedroni (1999, 2004) tests allows for significant heterogeneity. For both tests, the null hypothesis is that there is no cointegration against an alternative that there is a co-integrating relationship.

### **3.5. Panel causality and post estimation diagnostic tests**

Having established the order of integration through the panel root tests and the presence of a long-run equilibrium through the panel cointegration tests, the next step is to test the direction of causality, through dynamic panel causality tests. The tests for causality, however, are dependent on the panel cointegration results (Granger, 1988; Engle & Granger, 1987; Stock & Watson, 1993). In the case of no cointegration, a panel VAR equation is estimated. The panel VAR equation is similar with Equation 2 above but without the error correction component<sup>4</sup>. In a panel VAR, only short-run coefficients are estimated and short-run causality inferred. There are four categories of results expected from the panel VAR/VECM Granger causality approach, namely: (i) joint causality, where the coefficient of the error correction term (ECT) is negative and significant; (ii) short-run causality, when the coefficient of short-run explanatory variables are statistically significant; (iii) long-run causality, when the coefficient of long-run explanatory variables are statistically significant and (iv) strong causality, which is a situation where there is a presence of ECT, and both short-run and long-run causality.

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<sup>4</sup>A panel VECM is restricted panel VAR.

After estimating the VECM, causality can be inferred in three main ways. Firstly, by checking the regressors' and ECT  $t$ -statistics. Short-run causal effects are inferred if the regressors'  $t$ -statistics are statistically significant while long-run causality is inferred when the coefficient of ECT is negative and statistically significant. Secondly, the use of Granger/Wald causality tests. This a short-run causality test, which is conducted on the lagged explanatory variables. The null hypothesis is that the coefficient(s) of the lagged regressor(s) or explanatory variables is equal to zero against the alternative hypothesis that the coefficient(s) are not equal to zero. The null hypothesis is rejected if the probability value of the  $\chi^2$  statistics is less than 5 percent ( $p \leq 0.05$ ). Thirdly, causality can be tested using the pairwise Granger causality test. This was specifically developed to test the direction of causality. The null hypothesis is that there is no Granger causality against the alternative that the null hypothesis is not true. The null hypothesis is rejected if the probability value of the  $F$ -statistics is less than 5 percent ( $p \leq 0.05$ ).

Normally, the three Granger causality inferential methods described above lead to the same conclusion. This study used the first and the second method. The third method was used for robust checks only. The final step in the panel Granger causality test in the VECM framework is to run diagnostic tests. For the residual diagnostics, the study ran the serial auto-correlation, normality and heteroskedasticity tests.

#### **4. Data Sources and Definitions of Variables**

The class of poverty measure used in this study follows the work of Foster *et al.* (1984), which is usually referred to as monetary measures of poverty. The headcount index, or the poverty rate, measures the proportion of households in a population with income per person below the poverty line. It is a measure of absolute or extreme poverty (Todaro & Smith, 2012). It

measures the prevalence of poverty, in terms of the spread of poverty within the population (Schaffner, 2014).

The poverty headcount rate was obtained from the recently released World Bank poverty and inequality dataset (PovcalNet). The poverty measures in the PovcalNet dataset are estimated by using a programme developed by Chen and Ravallion (2001). The compilation is based on primary information from nationally representative living-standard household surveys. The poverty data is estimated by using a combination of purchasing power parity (PPP) and exchange rates for household consumption. The poverty measures used in this paper are based on the international poverty line US\$1.90 a day in US dollars in 2011 PPP.

The PovcalNet dataset provides triennial estimates of poverty and inequality measures from 1981 to 2008. Thereafter, there is annual data from 2010 and 2013. Since poverty headcount rate is available every three years between 1981 and 2008, and following Alvi and Senbeta (2011), we took three-year averages of our economic growth and foreign aid proxies over the period 1981-2008 and two-year average thereafter. As a result, our total panel has 82 developing countries covering 12 periods (from 1981 to 2013). Appendix A lists the countries in the sample, which chosen based on data availability.

Foreign aid is generally defined as public and private funds given to developing countries – with the main purpose of improving economic development and welfare (Clunies-Ross *et al.*, 2009, p. 590). The study used the standard definitions used by OECD-DAC. Official Development Assistance (ODA) and Official Aid (OA) include: (i) grants and (ii) concessional loans of more than a year's term, and with a 25 per cent or more grant-element. The proxy used for foreign aid is ODA as a percentage of the recipient country's Gross National Income (GNI).

The foreign-aid data was obtained from the Organisation for Economic Co-operation and Development's Development Assistance Committee (OECD-DAC). Following Pradhan and Arvin (2015), economic growth is proxied by real income per capita at 2005 constant prices (GDP). Real GDP per capita is from the World Bank's Development Indicators (World Bank, 2017).

## 5. Empirical Analysis and Discussion of Results

### 5.1. Descriptive and cross-correlation analysis

The data has been linearised, by taking natural logarithms. Table 1 shows the descriptive statistics for the logged and normalised data in terms of the measures of central tendency (mean, minimum, and maximum; dispersion (standard deviation) and normality (skewness, kurtosis and normality tests).

**Table 1: Descriptive statistics**

Variable	Obs.	Mean	Std.	Min.	Max.	Skew.	Kur.	JB	Pro.
Poverty rate	964	2.98	1.33	-3.00	4.57	-1.25	4.67	363.09	0.00
ODA	964	1.03	1.90	-7.70	4.78	-1.08	4.02	229.41	0.00
GDP per capita	964	7.29	1.06	4.93	9.58	0.15	2.03	41.48	0.00

**Notes:** The sample comprises 82 developing countries for the period 1981-2013. These summary statistics are based on the natural logs of the variable, in levels. The abbreviations ODA stands for official development assistance; GDP: gross domestic product; Obs.: observations; Std.: standard deviations; Min.: minimum; Max.: maximum; Skew.: skewness; Kur.: kurtosis; JB: Jarque-Bera statistics; Pro.: probability.

As shown in Table 1, the summary of the statistics for the three variables show minimum variations across the 82 sampled developing countries of the world from 1981 to 2013. In terms of normality tests, GDP per capita mirrors normal skewness and platykurtic (with a kurtosis of less than 3). Both poverty rate and ODA have a long-left tail (negative skewness) and leptokurtic (with a kurtosis of more than 3). The Jarque-Bera statistics, which measure the difference of the skewness and kurtosis of the series with those from the normal distribution,



show that the three variables are not normally distributed. This suggests the possibilities of outliers in the data.

Table 2 shows the Pearson correlation matrix for the three variables used in this study. As expected, GDP per capita and poverty rate and GDP per capita and ODA present negative correlation coefficients of -0.69 and -0.71 respectively. The correlation coefficient for ODA and poverty rate is positive (0.50). This suggests that poverty rate and ODA in this sample move in the same direction or are positively correlated.

**Table 2: Correlation matrix**

Variables	Poverty rate	ODA	GDP per capita
Poverty rate	1.00	0.50	-0.69
ODA		1.00	-0.71
GDP per capita			1.00

**Notes:** The sample comprises 82 developing countries for the period 1981-2013. These summary statistics are based on the natural logs of the variable, in levels. The abbreviations ODA stands for official development assistance; GDP: gross domestic product.

## 5.2. Panel unit root test results

The first step in panel Granger causality analysis is to test the stationarity of the variables. Inclusion of nonstationary panels in the estimation might lead to spurious regressions (Gujarati & Porter, 2009; Baltagi, 2013). Though the IPS is preferred due to its ability to cater for individual country heterogeneity, four panel data unit root tests are used for robustness.

The tests were applied on the three variables in levels and first differences and specifications included (i) no trend and intercept, (ii) with intercept only, and (iii) with intercept and trend. The LLC (2002) test assumes that the unit root process for the panel is common or homogenous, while the other three treat the panel as heterogeneous (individual unit root). In

all the four tests, we test the null hypothesis that the variable is non-stationary (meaning that it contains a unit root). Thus, rejection of the null means the variable in question is stationary.

Table 3 shows that results of the four panel unit root tests, namely LLC, IPS, ADF – Fisher, and PP – Fisher.

**Table 3: Panel unit root tests**

Test Statistics	Variables					
	Level data			First difference data		
	POV	ODA	GDP	POV	ODA	GDP
<i>Case 1: No trend and intercept</i>						
LLC	-6.76***	-6.15***	11.98	-10.81***	-26.61***	-6.92***
IPS	-	-	-	-	-	-
ADF	303.48***	213.32***	36.85	338.11***	584.13***	302.42***
PP	402.06***	246.96***	58.30	565.90***	749.67***	413.98***
<i>Case 2: With intercept only</i>						
LLC	3.64	-17.44***	0.06	-9.87***	-20.73***	-13.64***
IPS	8.63	-1.24	6.40	-3.48***	-7.76***	-5.02***
ADF	88.11	177.03	98.66	235.42***	331.77***	273.04***
PP	92.42	145.74	139.66	456.80***	503.55***	391.75***
<i>Case 3: With intercept and trend</i>						
LLC	-4.95	-32.86***	-10.91***	-16.05***	-17.46***	-19.85***
IPS	3.74	-3.21***	0.35	-2.47***	-3.00***	-5.40***
ADF	118.18	213.67***	180.91	254.52***	264.81***	297.14***
PP	186.61	211.76***	214.27	557.13***	573.71***	486.02***

**Notes:** \*\*\* denotes significance at the 1% level. The abbreviations ODA stands for official development assistance; GDP: gross domestic product; POV: poverty rate; LLC: Levine-Lin-Chu statistics; IPS: Im-Pesaran-Shin statistics; ADF: augmented Dickey-Fuller statistics; PP: Philips-Perron statistics.

As shown in Table 3, under the ‘no trend and intercept’ and ‘with intercept and trend’ panel unit specification, the ODA panel seems to be stationary. However, the IPS (the preferred test), does not confirm this result when we include ‘intercept only’. GDP and poverty rate panels are not stationary at level but stationary in first-difference. In summary, the three panels could be considered as integrated of order one,  $I(1)$ .

### 5.3. Cross-sectional dependency test results

Baltagi (2008) and Tekin (2012b) argue that the majority of causality studies suffer from estimation bias due to the use of econometric estimation techniques which do not take into account cross-sectional dependence. Table 4 shows the results of the Pesaran CD (2004) test for cross-sectional dependence.

**Table 4: Panel cross-sectional residual dependence test**

Variables	Test	Statistic	Probability
Poverty rate/ ODA/GDP	Breusch-Pagan LM	16446.56***	0.000
	Pesaran scaled LM	152.388***	0.000
	Pesaran CD	18.309***	0.000

Notes: \*\*\* denotes significance at the 1% level.

As shown in Table 4, all the CSD tests strongly reject the null that there is no correlation (cross-sectional interdependence) in variables or residuals within the sample. The results show evidence of cross-dependence in poverty levels across countries in the sample. This is expected given that the countries in the sample are developing countries, whose main characteristics are high levels of poverty and low per capita GDP. This also shows that the poverty rate, ODA, and GDP per capita variables appear to reveal some dynamics which are common to developing countries.

#### 5.4. Panel cointegration test results

Having found that the three variables are integrated of order one, the next step, before testing Granger causality, is to conduct cointegration tests. This is a test of whether there is a long-run relationship between the three variables (Granger, 1988; 2004). The study used the Pedroni (1999, 2004) panel cointegration tests. The Kao (1999) panel cointegration test was used to validate the presence of a long-run relationship between the three variables. For both the Pedroni (1999, 2004) and Kao (1999) panel cointegration tests, the null hypothesis is that there is no cointegration. The panel cointegration test results are shown in Table 5.

**Table 5: Panel cointegration test**

Test	Statistic	Dependent Variable		
		Poverty Rate	ODA	GDP
Pedroni (1999, 2004)	Panel v-Statistic	-4.40	0.05	-0.77
	Panel rho-Statistic	2.95	2.82	3.63
	Panel PP-Statistic	-2.37***	-3.27***	1.56***
	Panel ADF-Statistic	-3.89***	-4.15***	0.81***
	Group rho-Statistic	5.33	5.71	5.81
	Group PP-Statistic	-7.26***	-9.03***	-5.30***
	Group ADF-Statistic	-7.43***	-11.74***	-6.32***
Kao (1999)	ADF t-Statistic	-2.40***	-8.62***	-3.75***
<i>Inference</i>		<i>Cointegrated</i>	<i>Cointegrated</i>	<i>Cointegrated</i>

Notes: \*\*\* denotes significance at the 1% level.

As shown in Table 5, panel cointegration tests were conducted on each of the three equations with each of the variables; poverty rate, ODA and GDP assuming the role of the dependent variable and the others being explanatory variables. The panel cointegration test results show that four out of the seven Pedroni (1999, 2004) statistics reject the null of no cointegration at the 1 percent level of significance. According to Pedroni (2004), in a small N and small T sample, the group-ADF statistic performs better followed by a panel-ADF statistic while a panel-v statistic and panel-rho statistic perform poorly. The Kao (1999) panel cointegration test confirms the results of the Pedroni (1999, 2004) tests. It can therefore be concluded that there

is evidence of the existence of a long-run equilibrium relationship between the three variables when each of them is a dependent variable.

### 5.5. Panel causality test results

As explained in the literature on panel Granger causality tests (Engle & Granger, 1987; Granger, 2004; Dumitrescu & Hurlin, 2012), when the variables are stationary but not cointegrated, the Granger causality test could be done with the panel VAR framework. However, if the variables are integrated of the same order and cointegrated, a panel VECM can be applied to test both short-run and long-run causality. The results of both the Pedroni (1999, 2004) and Kao showed evidence that foreign aid, poverty rate and GDP per capita are cointegrated, therefore, a dynamic panel data model using the VECM Granger causality framework was estimated. Before the panel VECM estimation, the number of optimal lags was established as 2, using the Schwarz information criteria, under the unrestricted panel VAR model. The panel Granger causality test results, based on the panel VECM, are shown in Table 6.

**Table 6: Panel Granger causality based on VECM estimation**

Dependent Variable	Direction of Causality/Explanatory Variables				Diagnostic tests: Serial Correlation
	Short run $\chi^2$ statistics (p-value)			Long run Coefficient (t-statistics)	LM-Test (p-value)
	$\Delta$ POV	$\Delta$ ODA	$\Delta$ GDP	ECT	
$\Delta$ POV	-	0.626 (0.429)	13.097*** (0.000)	-0.001 (-0.882)	5.508 (0.788)
$\Delta$ ODA	0.187 (0.666)	-	17.513*** (0.000)	-0.164*** (-9.286)	5.508 (0.788)
$\Delta$ GDP	3.687* (0.055)	15.971*** (0.000)	-	-0.001 (-0.271)	12.220 (0.201)

Notes: *Short Run*-The sum of the lagged coefficients for the respective short-run changes in the independent variable(s) are shown with their corresponding Wald  $X^2$  statistics and p-values in brackets (). For the *long-run*, coefficients of the ECT are reported and in brackets () are the t-statistics. \*\*\*, \*\*, and \* denote a significance of 1%, 5% and 10%, respectively.

As illustrated in Table 6, the short-run causality tests are performed through the Wald  $\chi^2$  statistics while long-run causality is inferred from the coefficients of ECT and corresponding  $t$ -statistics. In the short-run, there is evidence of (i) a bidirectional causal relationship between GDP per capita and headcount poverty rate (GDP $\leftrightarrow$ POV), (ii) a unidirectional causal relationship from GDP per capita to foreign aid (GDP $\rightarrow$ ODA) and (iii) unidirectional causality from poverty rate to foreign aid (POV $\rightarrow$ ODA). Our short-run results can be contrasted with those of Arvin and Barillas (2002, p. 2154) who found that “*aid does not have a significant impact on poverty nor does poverty affect the level of aid that is given.*”<sup>5</sup> Pradhan and Arvin (2015) found evidence of short-run unidirectional causality from foreign aid to economic growth.

For the long-run causality results, only the coefficient of the ECT, when foreign aid is the dependent variable is negative and statistically significant. This implies that (i) foreign aid tends to converge to its long-run equilibrium path in response to changes in per capita GDP and headcount poverty rates and (ii) both GDP per capita and poverty rate jointly Granger cause foreign aid in the long-run (GDP & POV  $\rightarrow$  ODA). In contrast, there is no evidence of a long-run relationship or causality when  $\Delta$ POV and  $\Delta$ GDP are the dependent variables.

Both the short- and long-run Granger causality results reinforce each other, confirming that causality runs from GDP per capita and poverty rate to foreign aid. The short-run causality from GDP per capita to ODA suggests that donors mainly consider this variable in their short-term foreign aid allocation. The long-run joint causality for poverty and GDP to ODA suggests that aid is generally allocated to developing countries with high levels of poverty and lower

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<sup>5</sup> Please note that the Arvin and Barillas (2002) study, by its specification, only focused on the short-run Granger causality.

GDP per capita. Furthermore, decisions on aid allocation are taken over a long-time horizon while changes in poverty levels sometimes take generations. The lack of a long-run relationship between poverty rate and foreign aid when  $\Delta\text{POV}$  is the dependent variable implies that foreign aid is not a long-term solution for poverty.

Lastly, after estimation of the panel VECM equations, it is important to perform panel data serial correlation tests, to conform the validity of the panel VECM estimations (Wooldridge, 2002; Muye & Muye, 2016). We used the Breusch-Godfrey serial correlation (LM) Test. The null hypothesis is that there is no serial correlation against the alternative that there is serial correlation. As shown in Table 6 (column 6), all three models (equations) do not have serial correlation. The p-values for all three equations are more than 10 percent and therefore we cannot reject the null hypothesis (we therefore accept the null hypothesis), which means that all the equations are free from serial correlations.

## **6. Concluding Remarks**

This study investigates the causal relationship between foreign aid and poverty reduction in 82 developing countries over the period 1981-2013. The study used the Pedroni (1999, 2004) panel cointegration and the dynamic VECM Granger causality tests, in a trivariate setting with real GDP per capita as an intermittent variable. The main findings from the panel VECM Granger causality analyses are that in the short-run, there is evidence of (i) a bidirectional causal relationship between GDP per capita and headcount poverty rate; (ii) a unidirectional causal relationship from GDP per capita to foreign aid; and (iii) unidirectional causality from poverty rate to foreign aid. In the long-run, the study found that (i) foreign aid tends to converge to its long-run equilibrium path in response to changes in per capita GDP and headcount poverty rates and (ii) both GDP per capita and poverty rate jointly Granger cause foreign aid

in the long-run. There was no evidence of a long-run relationship or causality when poverty rate and GDP per capita, were the dependent variables.

The strong and joint causal effect from poverty rate and GDP per capita to foreign aid could be a confirmation that the majority of aid is directed towards poor countries. From the 1990s to the promulgation of the MDGs in 2000, there has been a shift of the foreign aid allocation motive towards poverty reduction (Riddell, 2008; Schaffner, 2014). Furthermore, foreign aid can be associated with the aid dependency syndrome, encouragement of rent seeking or corruption, Dutch disease and the crowding-out of local investments (Friedman, 1958; Bauer, 1972; Collier, 2007; Moyo, 2009); which tend to limit its impact in reducing extreme poverty.

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## APPENDIX A: SAMPLE OF COUNTRIES AND THEIR REGIONS

COUNTRY	REGION	COUNTRY	REGION
China	East Asia and Pacific	Angola	Sub-Saharan Africa
Fiji	East Asia and Pacific	Benin	Sub-Saharan Africa
Indonesia	East Asia and Pacific	Botswana	Sub-Saharan Africa
Lao People's Democratic Republic	East Asia and Pacific	Burkina Faso	Sub-Saharan Africa
Malaysia	East Asia and Pacific	Burundi	Sub-Saharan Africa
Mongolia	East Asia and Pacific	Cabo Verde	Sub-Saharan Africa
Papua New Guinea	East Asia and Pacific	Cameroon	Sub-Saharan Africa
Philippines	East Asia and Pacific	Central African Republic	Sub-Saharan Africa
Thailand	East Asia and Pacific	Chad	Sub-Saharan Africa
Vietnam	East Asia and Pacific	Comoros	Sub-Saharan Africa
Albania	Eastern Europe and Central Asia	Congo, Democratic Republic of	Sub-Saharan Africa
Turkey	Eastern Europe and Central Asia	Congo, Republic of	Sub-Saharan Africa
Bolivia	Latin America and the Caribbean	Cote d'Ivoire	Sub-Saharan Africa
Brazil	Latin America and the Caribbean	Ethiopia	Sub-Saharan Africa
Chile	Latin America and the Caribbean	Gabon	Sub-Saharan Africa
Colombia	Latin America and the Caribbean	Gambia, The	Sub-Saharan Africa
Costa Rica	Latin America and the Caribbean	Ghana	Sub-Saharan Africa
Dominican Republic	Latin America and the Caribbean	Guinea	Sub-Saharan Africa
Ecuador	Latin America and the Caribbean	Guinea-Bissau	Sub-Saharan Africa
El Salvador	Latin America and the Caribbean	Kenya	Sub-Saharan Africa
Guyana	Latin America and the Caribbean	Lesotho	Sub-Saharan Africa
Jamaica	Latin America and the Caribbean	Liberia	Sub-Saharan Africa
Mexico	Latin America and the Caribbean	Madagascar	Sub-Saharan Africa
Nicaragua	Latin America and the Caribbean	Malawi	Sub-Saharan Africa
Panama	Latin America and the Caribbean	Mali	Sub-Saharan Africa
Peru	Latin America and the Caribbean	Mauritania	Sub-Saharan Africa
Suriname	Latin America and the Caribbean	Mauritius	Sub-Saharan Africa

Venezuela, Republica Bolivariana de	Latin America and the Caribbean		Mozambique	Sub-Saharan Africa
Algeria	Middle East and North Africa		Namibia	Sub-Saharan Africa
Egypt, Arab Rep.	Middle East and North Africa		Niger	Sub-Saharan Africa
Iran, Islamic Republic of	Middle East and North Africa		Nigeria	Sub-Saharan Africa
Jordan	Middle East and North Africa		Rwanda	Sub-Saharan Africa
Morocco	Middle East and North Africa		Senegal	Sub-Saharan Africa
Tunisia	Middle East and North Africa		Sierra Leone	Sub-Saharan Africa
Bangladesh	South Asia		South Africa	Sub-Saharan Africa
Bhutan	South Asia		Sudan	Sub-Saharan Africa
India	South Asia		Swaziland	Sub-Saharan Africa
Nepal	South Asia		Tanzania	Sub-Saharan Africa
Pakistan	South Asia		Togo	Sub-Saharan Africa
Sri Lanka	South Asia		Uganda	Sub-Saharan Africa
			Zambia	Sub-Saharan Africa
			Zimbabwe	Sub-Saharan Africa