Mahembe & Mbaya Odhiambo, *Cogent Economics & Finance* (2019), 7: 1626321
https://doi.org/10.1080/23322039.2019.1626321

cogent economics & finance

GENERAL & APPLIED ECONOMICS | RESEARCH ARTICLE

Foreign aid, poverty and economic growth in developing countries: A dynamic panel data causality analysis

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Received: 10 January 2019
Accepted: 28 May 2019

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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 is 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.

Subjects: Economics and Development; Economics; Econometrics

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PUBLIC INTEREST STATEMENT

This paper examines the causal relationship between foreign aid, poverty and economic growth using a sample of 82 developing countries for the period 1981–2013. It uses recent dynamic panel data estimation techniques, which include panel unit roots, cross-sectional dependence, cointegration and Granger causality tests. The panel VECM framework was used for causality investigation. Panel cointegration tests confirm the existence of a long-run cointegrated relationship between the three variables. Causality test results can be summarised as follows: 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 aid; and (c) unidirectional causality from poverty to aid. In the long-run, the study found that (a) 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 aid.

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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

1. Introduction

The history of foreign aid can be traced as far back as the late 1870s and early 1920s, when the United Kingdom (UK) began the discussion on how to finance the development of poor countries which were then British colonies (Hjertholm & White, 1998). However, the provision of development aid, as it is known today, started after World War II (World Bank, 1998). In 1947, the USA established and funded the Marshall Plan which was aimed at rebuilding Europe after the war (McGillivray, Feeny, Hermes, & Lensink, 2006). In the 1960s, ODA constituted around 55% of all net disbursements by DAC countries but has decreased to around 30% in recent years. The proportion of private flows, which include foreign direct investment (FDI) and commercial bank loans, has grown from 29% to 57% over the same period. Despite these shifts, Arvin and Lew (2015, p. 1) still believe 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 has also caused huge and polarising debates on the effectiveness of foreign aid in delivering on the developmental goals (sustained economic growth and poverty reduction). Poverty reduction has additionally emerged as an explicit objective since the introduction of the Millennium Development Goals (MGDs) (Ravallion, 2016; Sachs, 2005). 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% 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 these studies are focused on the impact of foreign aid on economic growth, though there has been a recent surge of research looking at the effectiveness of foreign aid on poverty reduction.

A review of literature has shown that there is an economic link between foreign aid, economic growth and poverty. Though the empirical results on causality are mixed, the majority of the studies reviewed showed that (i) foreign aid causes poverty reduction, (ii) foreign aid leads to economic growth and (iii) growth causes decreases in poverty. However, the main gap in this literature is that, to the best of our knowledge, there has not been a study which has examined the causal relationships between these three variables concurrently.

This paper adds to a small body of AEL which examines the direction of causality between foreign aid, economic growth and poverty. Specifically, the paper aims to fill the gap, where causality is examined in a panel trivariate setting. The study uses recent dynamic panel data estimation techniques, including those methods which test for stationarity, cointegration and short- and long-run causality. This paper, therefore, investigates the dynamic causal relationships between foreign aid, economic growth and poverty in developing countries.

The rest of the paper is organised as follows: Section 2 presents theoretical literature on the link between foreign aid, economic growth and poverty, while a survey of empirical literature is presented in Section 3. Section 4 presents the model specification and estimation methodology, Section 5 discusses the data, Section 6 covers the empirical results, while Section 7 offers concluding remarks.

2. Theoretical link between Foreign aid, economic growth and poverty

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 (Dollar & Kraay, 2002; Feeny, 2003; Norton, 2002).

The formalisation of foreign aid in the 1940s and the subsequent allocation criteria up to the late 1980s were 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 developing countries into self-sustaining economic growth (Lewis, 1954; Nurske, 1953). 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).

However, other scholars argue that 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 (Bauer, 1972; Collier, 2007; Friedman, 1958; Moyo, 2009). All these tend to limit its impact in reducing extreme poverty.

Apart from economic growth, other channels through which foreign aid affects poverty include: (i) 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 other things (Mahembe & Odhiambo, 2017). This study, however, is aimed at examining the causal relationship between foreign aid, poverty and economic growth. We briefly discuss some relevant empirical studies below.

3. Survey of empirical literature

3.1. 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 the real value of aid “causes” a reduction in poverty.

Arvin and Barillas (2002) employed Granger causality analysis 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 showed that aid was not affecting poverty and vice versa. For the 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).

3.2. Studies on causality between Foreign aid and economic growth

A recent study by Forson, Buracom, Baah-Ennumh, Chen, and Carsamer (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 found evidence of an independent short-run causal relationship between the two variables. However, a long-run unidirectional causal relationship was discovered 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 relationships between foreign aid, trade openness and economic growth in African least developed countries (LDC) for the period between 1970 and 2010. Tekin (2012a) used the seemingly unrelated regressions (SUR) estimator proposed by Zellner (1962). The results of 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.

Pradhan and Arvin (2015) used a panel VECM framework for the period 1961–2012 to investigate the causal relation between foreign and economic growth and other two variables. The panel cointegration tests found evidence of the existence of a long-run equilibrium relationship amongst the four variables, and in the short-run, foreign aid was found to unidirectionally Granger cause economic growth. The was evidence of bidirectional causality between foreign aid and economic growth in the long-run.

3.3. 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, Agnello, and Link (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 and the long run, and (ii) poverty 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.

In summary, both the theoretical and empirical literature have shown that there is an economic link between foreign aid, economic growth and poverty. Though the empirical results on causality are mixed, the majority of the studies reviewed showed that (i) foreign aid causes poverty reduction, (ii) foreign aid leads to economic growth and (iii) growth causes decreases in poverty. However, the main gap in this literature is that, to the best of our knowledge, there has not been a study which has examined the causal relationships between these three variables concurrently.

4. Model specification and econometric methodology

The main objective of this study is to examine the causal relationships between 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 supports 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 also 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. Lastly, there is a possibility that the system can have evidence of long-run causality without short-run causality. This is, however, an exception.

4.1. Model specification

The model specification follows that by Holtz-Eakin, Newey, and Rosen (1988), and describes the causal relationships between foreign aid, poverty and economic growth, as shown in Equation (1),

$$V = f(ODA, GDP) \tag{1}$$

where *POV* is the 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).

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

where *POV*, *ODA*, and *GDP* are as defined in Equation (1), which alternate in taking the dependent and explanatory variable roles; Δ is the first difference operator $(\mathrm{I}-L)$; i = 1, ..., N; t = 1, ..., T; $\alpha_s, \beta_s,$ and λ_s (j = 1 ..., 3) are parameters to be estimated; ε_{jt} (j = 1 ..., 3) are white noise error terms; ECT_{it-1} are the lagged values of the error correction terms from the co-integration regressions, while λ_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 (β_s) using the partial χ^2 statistics of the Wald test (Wald, 1943), while the long-run causality is tested through the lagged co-integrating vectors ECT_{t-j} (λ_s).

4.2. Panel data unit root tests

One of the key requirements for panel VECM is that the variables' stationarity properties must 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, Lin, and Chu (2002) (LLC) and Im, Pesaran, and Shin (2003) (IPS). Though both tests are based on the augmented Dickey–Fuller (ADF) principle (see Equation 3), the main difference between the two is that the former assumes homogeneous unit roots across all cross-sections, while the latter allows for heterogeneity (Baltagi, 2013, p. 276).

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

In Equation (3), d_{mt} denotes the vector of deterministic variables, ρ_i is the lag-order which is permitted to vary across cross-sections and is determined by choosing a ρ_{max} and then uses a t-statistic of θ_{iL}; $\varepsilon_{i,t}$ is assumed to be independently distributed across i and t, $i = 1, \ldots, N$, $t = 1, \ldots, T$.

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 tests are that the variables must be stationary and integrated of order one (i.e. $\boldsymbol{I}(1)$).

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: the Fisher-ADF and Fisher-Phillips-Perron (Fisher-PP) (Choi, 2001; Madala & Wu, 1999) panel unit root tests.

4.3. 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 usually valid for large T and small N (Pesaran, 2004). The latter is 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[1] in literature are the Akaike information criterion (AIC) (Akaike, 1974) and the Schwarz information criterion (SC) (Schwarz, 1978). Other researchers have 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 SC performs better. Winker and Maringer (2005) showed that the SC performs relatively well in the VECM framework. This study, therefore, used the SC and the unrestricted VAR model to determine the optimal lag selection. The AIC was also used for robustness checks.

4.4. 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, a 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). 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 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 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 allow for significant heterogeneity. For both tests, the null hypothesis is that there is no cointegration against an alternative hypothesis that there is a co-integrating relationship.

4.5. 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 (Engle & Granger, 1987; Granger, 1988; Stock & Watson, 1993). In the case of no cointegration, a panel VAR equation is estimated. The panel VAR equation is similar to Equation 2 but without the error correction component.[2] In a panel VAR, only short-run coefficients are estimated, and short-run causality is 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 coefficients of short-run explanatory variables are statistically significant; (iii) long-run causality, when the coefficients 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.

After estimating the VECM, causality can mainly be inferred in three 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, VECM, causality can be inferred by the use of Granger/Wald causality test. 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 are equal to zero against the alterative hypothesis that the coefficient(s) are not equal to zero. The null hypothesis is rejected if the probability value of the χ^2 statistic is less than 5% ($p \leq 0.05$). Thirdly, causality can be tested using the pairwise Granger causality test which 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*-statistic is less than 5% ($p \leq 0.05$).

Normally, the three Granger causality inferential methods described above lead to the same conclusion. This study used the first and the second methods, while 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.

5. Data sources and definitions of variables

The class of poverty measure used in this study follows the work of Foster, Greer, and Thorbecke (1984), usually referred to as a monetary measure 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 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 of 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, annual data are available between 2010 and 2013. Since a 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 averages 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 is 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, Forsyth, & Huq, 2009, p. 590). The study used the standard definitions used by the OECD-DAC (Organisation for Economic Co-operation and Development's Development Assistance Committee). 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% 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 were obtained from the 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).

6. Empirical analysis and discussion of results

6.1. Descriptive and cross-correlation analysis

The data have 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).

As shown in Table 1, the summaries 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, the GDP per capita mirrors normal skewness and is platykurtic (with a kurtosis of less than three). Both the poverty rate and ODA have a long-left tail (negative skewness) and are leptokurtic (with a kurtosis of more than three). The Jarque-Bera statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. This shows that the three variables are not normally distributed, which suggests the possibility of outliers in the data.

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

6.2. Panel unit root test results

The first step in panel Granger causality analysis is to test for the stationarity of the variables. Inclusion of nonstationary panels in the estimation might lead to spurious regressions (Baltagi, 2013; Gujarati & Porter, 2009). 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 the 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

Table 1. Descriptive statistics

Variable	Obs.	Mean	Std.	Min.	Max.	Skew.	Kur.	JB	Pro.
Poverty rate	981	2.95	1.38	−3.00	4.57	−1.32	4.95	442.56	0.00
ODA	967	1.04	1.90	−7.70	4.78	−1.08	4.02	229.75	0.00
GDP per capita	981	7.30	1.06	4.79	9.58	0.11	2.02	41.56	0.00

The sample comprises 82 developing countries, with averaged data for the period 1981–2013. These summary statistics are based on the natural logs of the variables, in levels. The abbreviation 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.

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

The sample comprises 82 developing countries for the period 1981–2013. These summary statistics are based on the natural logs of the variables, in levels. The abbreviation ODA stands for official development assistance; GDP means gross domestic product.

other three treat the panel as heterogeneous (individual unit root). We test the null hypothesis that the variable is non-stationary (meaning that it contains a unit root) in all the four tests. Thus, rejection of the null hypothesis means the variable in question is stationary. Table 3 shows the results of the four-panel unit root tests, namely the LLC, IPS, ADF—Fisher, and PP—Fisher.

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).

6.3. 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 (2004) test for cross-sectional dependence.

As shown in Table 4, all the CSD tests strongly reject the null hypothesis 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.

6.4. 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 tests 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 also used to validate the presence of a long-run relationship between the three variables. For both the Pedroni (1999, 2004)

Table 3. Panel unit root tests

Test statistics	Variables					
	Level data			First difference data		
	POV	ODA	GDP	POV	ODA	GDP
Case 1: No trend and intercept						
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***
Case 2: With intercept only						
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***
Case 3: With intercept and trend						
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***

*** 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-Pessaran-Shin statistics; ADF: augmented Dickey–Fuller statistics; PP: Philips–Perron statistics.

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

*** denotes significance at the 1% level.

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.

As shown in Table 5, panel cointegration tests were conducted on each of the three equations with each of the variables: the 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 hypothesis of no cointegration at the 1% 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.

6.5. Panel causality test results

As explained in the literature on panel Granger causality tests (Dumitrescu & Hurlin, 2012; Engle & Granger, 1987; Granger, 2004), 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

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***
Inference		*Cointegrated*	*Cointegrated*	*Cointegrated*

*** denotes significance at the 1% level.

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 two, using the Schwarz information criteria under the unrestricted panel VAR model. The panel Granger causality test results, based on the panel VECM framework, are shown in Table 6.

As illustrated in Table 6, the short-run causality tests are performed through the Wald χ^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↔POV), (ii) a unidirectional causal relationship from GPD per capita to foreign aid (GDP→ODA) and (iii) a unidirectional causality from poverty rate to foreign aid (POV→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.*"[3] Pradhan and Arvin (2015) found evidence of short-run unidirectional causality from foreign aid to economic growth.

Table 6. Panel Granger causality based on VECM estimation

Dependent variable	Direction of causality/explanatory variables				Diagnostic tests: Serial correlation
	Short run χ^2 statistics (p-value)			Long run coefficient (*t*-statistics)	LM-test (p-value)
	ΔPOV	ΔODA	ΔGDP	ECT	
ΔPOV	-	0.626 (0.429)	13.097*** (0.000)	−0.001 (−0.882)	5.508 (0.788)
ΔODA	0.187 (0.666)	-	17.513*** (0.000)	−0.164*** (−9.286)	5.508 (0.788)
ΔGDP	3.687* (0.055)	15.971*** (0.000)	-	−0.001 (−0.271)	12.220 (0.201)

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^2statistics and p-values in brackets (). For the ***long-run,*** coefficients of the ECT are reported and in brackets () are the t-statistics. The ***, **, and * denote a significance of 1%, 5% and 10%, respectively.

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 head-count poverty rates, and (ii) both GDP per capita and poverty rate jointly Granger cause foreign aid in the long-run (GDP & POV → ODA). In contrast, there is no evidence of a long-run relationship or causality when ΔPOV and ΔGDP 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 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 ΔPOV 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 confirm 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 alterative that there is serial correlation. As shown in Table 6 (column 6), all three models (equations) do not have serial correlations. The p-values for all three equations are more than 10%, 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.

7. Conclusions and implications of results

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 GPD 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. Lastly, the study found a strong joint causal flow from poverty rate and GDP per capita to foreign aid.

These results compare favourably with existing empirical literature. This study's short-run results can be contrasted with those of Arvin and Barillas (2002) and Pradhan and Arvin (2015), while long-run causality results are in line with findings by Asteriou (2009) and Perez-Moreno (2016).

The short-run causality from GDP per capita to foreign aid suggests that donors mainly consider this variable in their short-term foreign aid allocation. The long-run joint causality from poverty and GDP to foreign aid implies that aid is generally allocated to developing countries with high levels of poverty and a lower GDP per capita. This result could be a confirmation that the majority of aid is directed towards poor countries. It is in line with the MDGs and SDGs call for a shift in foreign aid allocation motive towards poverty reduction (Riddell, 2008; Schaffner, 2014). Furthermore, the long-run causality from poverty and GDP per capita to foreign aid suggests that decisions on aid allocation are taken over a long-time horizon, and that changes in poverty levels sometimes take generations. The lack of a long-run relationship between poverty rate and foreign aid, when change in poverty rate is the dependent variable indicates that foreign aid is not a long-term solution for poverty.

Funding
The authors received no direct funding for this research.

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Citation information
Cite this article as: Foreign aid, poverty and economic growth in developing countries: A dynamic panel data causality analysis, Edmore Mahembe & Nicholas Mbaya Odhiambo, *Cogent Economics & Finance* (2019), 7: 1626321.

Notes

1. Other lag length selection methods include: Sequential-modified LR test statistic (LR); Final prediction error (FPE); and Hannan-Quinn information criterion (HQ).
2. A panel VECM is restricted panel VAR.
3. Please note that the Arvin and Barillas (2002) study, by its own specification, only focused on the short-run Granger causality.

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Appendix A. Sample of countries and their regions

COUNTRY	REGION	COUNTRY	REGION
China	East Asia and Pacific	Angola	
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

(*Continued*)

COUNTRY	REGION	COUNTRY	REGION
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

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