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The Impact of Official Development Assistance on Welfare of Low and Middle Income Countries

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Abstract: *This study investigates the Impact of Official Development Assistance (ODA) on the welfare of low- and middle-income countries (LMICs), measured through the Human Development Index (HDI). Using annual panel data from 1999 to 2023, the study incorporates Foreign Direct Investment (FDI), Inflation (INF), and Access to Electricity (ACE) as complementary macroeconomic factors. The Feasible Generalized Least Squares (FGLS) method was performed after detecting for Cross-sectional dependency (CD) and panel (CIPS) unit root tests. Empirical results revealed that ODA has a significant positive effect on HDI. FDI, ACE was also positively influencing HDI. In contrast, INF showed a negative relationship with HDI with a coefficient of –0.046, reducing the real benefits of ODA. These findings suggest that while ODA improves welfare, its effectiveness is maximized when supported by increased FDI, expanded electricity access, and stable price levels. Policy makers should prioritize ODA towards human capital, infrastructure, and institutional reforms, while implementing macroeconomic measures to control inflation and attract productive investment for sustained welfare gains.*

Introduction

Official Development Assistance (ODA) is the flow of funds (primarily from official providers) with the principal purpose of promoting the economic development and welfare of developing countries, as defined by the Organization for Economic Co-operation and Development (OECD). According to the OECD, ODA refers to either grants or loans that are issued by a bilateral client or through a multilateral intergovernmental organization, with a grant element of 25% (OECD, 2008). ODA has been a policy tool used historically in various contexts often serving as a humanitarian obligation or a strategic tool for soft power and has also acted as a significant contributor to health, education, infrastructure, governance reform, and institutional capacity in recipient countries (Sachs et al., 2004; Goldin et.al, 2002). However, ODA effects are neither linear nor universal in a positive direction, but are conditioned by a number of mediating variables, including governance, institutional strength, absorptive capacity, and economic performance (Burnside & Dollar 2000; Erkinharju, 2021). In weak and corrupt institutions, foreign aid can be lost, stolen, ineffectively used, or create aid dependency instead of sustainable growth (Goldin et al, 2002; Shirazi et.al, 2009). ODA in Sub-Saharan Africa is only significantly associated with HDI through domestic institutions. Where accountability of domestic institutions is lacking, ODA can have negligible and negative effects on welfare outcomes (Berhane, 2017).

ODA effects are also heterogeneous by income classifications. Many middle-income countries (MICs), particularly those falling into the “middle-income trap”, show declining marginal utility of ODA. Middle-income countries often need more complicated aid packages, however, as actual need changes to packages that include innovation, institutional restructuring, and technological development, rather than basic service provisions, (Hara, 2023). Consequently, the sectoral breakdown of aid matters more to consider in terms of developmental returns, be it a focus on infrastructure, social policy, or institutional reform. Further, as indicated by Ivaldi and Santagata (2019), ODA welfare effects are also conditioned by macroeconomic variables, such as starting GDP per capita and political stability. Moreover, in terms of how ODA translates into human development, a country's institutional environment is very likely to be more central. The effective use of ODA, involves coordinating across policies and creating institutional synergies. ODA by itself may not have sharp impacts, however, considering ODA in combination with other external or private flows, such as, remittances or foreign direct investment, has a synergistic effect particularly when the recipient country has a robust bureaucracy and fiscal transparency (Yiheyis & Woldemariam, 2020).

There remains a significant emphasis on ODA, despite some challenges. The Sustainable Development Goals (SDGs) are on the forefront of attention, which enhances the mere focus on foreign assistance, no longer just identifying the quantity of aid, but also in terms of quality, targeting and what alignments are like with national strategies. As Goldin et al. (2002) pointed out, the sooner we change conditions we have imposed on the future effectiveness of development strategies and the manner in which we choose to create participatory types of governance arrangements, the better ODA will be.

Literature Review

ODA led to growth and welfare improvement and ODA operates best when focused on countries with good institutions and policies that encourage economic growth. The institutional structure should feature policies and programs that are fashioned to maximize benefits (Burnside & Dollar, 2000). ODA has a considerable role in improving HDIs and more specifically in the more intuitive direction of improvements based on social service improvements to education and health, being two major components to welfare improvements (Sachs et al., 2004). While aid is successful in providing short-term gains in welfare, the effectiveness is conditional upon the absence of institutional weaknesses in recipient countries. While ODA can provide immediate gains in relation to education and health, the long-term impacts on welfare outcomes, like HDI, have been eroded by poor governance, corruption and policy-related limitations in low and middle income countries (Morrissey, 2001).

Foreign aid's effectiveness, supported by sound governance and institutional instruments, is essential to sustainable improvement on the Human Development Index. ODA may contribute to poverty, and some welfare improvement in short run but the costs associated with poor governance, corruption and lack of policy implementation eroded the potential long-term benefits associated with ODA (Rajah & Lim, 2015). The long-term welfare impacts were less certain as the quality of governance and institutional quality of the renewal process followed self-improvement however the welfare outcome of aid (such as HDI) could be significantly influenced if countries had sound governance that would allow aid to be effectively directed into productive and sustainable way (Bourguignon & Sundberg, 2007). The effectiveness of aid depends on a comprehensive approach to aid allocation that is independent of financial support which is required to establish the institutions that sustain the effectiveness of ODA (Morrissey, 2001).

Human welfare is subjected to different "drivers" including human capital, institutional quality, Foreign Direct investment, inflation and industry sectoral characteristics discussed briefly in this study. Countries with quality human capital use FDI and enhance the benefits to all while Countries with limited human capital see some people benefit at the expense of others (Herzer & Nunnenkamp, 2013). Infrastructure investments, especially electricity infrastructure investments support inclusive growth. The increase in welfare is most evident in developing countries where gaps in infrastructure and thereby access to services particularly in rural areas can be a significant constraint to development (Calderón & Servén, 2004). Improving electricity access in rural areas of Sri Lanka created significant changes in welfare and HDI, and that energy infrastructure is an important issue for rural development (Seneviratne & Sun, 2013). FDI in labour-intensive sectors decreases income inequality, thus offering enhanced welfare outcomes and a potential increase in HDI as Labour-intensive FDI generates low-skilled job opportunities for individuals and families in need of lifting themselves out of poverty (Kumari & Sharma, 2017). FDI can substantially affect welfare outcomes if it manages to ensure the benefits of FDI are shared widely within the host country, and that the economies can absorb and gain from foreign investment (Rewilak, 2017). FDI cannot reduce inequality on its own; it needs to be supported with policies to expand the welfare dimensions of FDI particularly the distribution of benefits over society-wide access to education, and improved access to health care. There is need for complementary policies to be in place, such as investment in human capital, infrastructure and other areas, so that FDI can be translated into inclusive growth and improved welfare, as measured by HDI (Azam & Raza, 2016).

Welfare in general, and in terms of HDI in particular, will be worse off as inflation can create barriers that impede welfare outcomes for the most vulnerable members of society (Easterly & Fischer, 2001). Inflation, particularly in developing economies, itself increases income inequality, and this reduction in income equality ultimately reduces overall welfare in society, and particularly among low-income households (Albanesi, 2007). Without substantial support from programs of social protection, low-income households have a much stronger negative welfare impact from inflation, thus effectively limiting their ability to recuperate from inflation losses (Younsi & Bechtini, 2018). When very unpredictable, inflation introduces uncertainty which also diminishes the real income of low-income households and diminishes economic stability. Inflation, when volatile, is often accompanied by some level of policy uncertainty and makes it difficult for households to plan and manage their finances. Such additional uncertainty causes greater inequality and worsens welfare improvements (Balcilar et al., 2021).

The study illustrates that Official Development Assistance (ODA) and welfare (HDI) are complicated in Low and Middle Income Countries (LMICs). In order for the impact of ODA to improve welfare, there are additional influences to consider: supply of electricity, FDI, and inflation. This study builds on the literature as it investigates the relationship between ODA and welfare empirically, as well as the consideration of other variables in order to provide an understanding and assessment of the mechanisms in which external aid can shift welfare in low-and middle-income countries. The current section will be followed by methodology of the research after which the results and the empirical relationship among the variables will be discussed in the section after methodology. Later this study will conclude and give policy recommendations.

Methodology

This research study investigates the impact of Official Development Assistance (ODA) on the Welfare of

Low- and Middle-income countries, specifically the five-country sample from Bangladesh, India, Nepal, Pakistan, and Sri Lanka over the time frame of 1999 to 2023. The dependent variable "Welfare" of countries proxy of Human Development Index (HDI) is taken, and Official Development Assistance (ODA), Inflation (INF), Foreign Direct Investment (FDI) and Access to Electricity (ACE) are the explanatory variables. This section will present a detail description of variables used in the study after which the paper has conducted necessary pre and post estimation techniques i.e the study checked the cross-sectional dependence among the countries proposed by Pesaran (2004), the order of integration of the variables through Cross-sectionally Augmented LM Pesaran-Shin (CIPS) test as proposed by Pesaran (2007), the correlation matrix is performed to examine the strength and direction of the linear relationship between each independent variables, VIF test is then used to measures how much the variance of a regression coefficient is inflated because of linear dependence with other independent variables in the model.

After the pre-estimation tests are performed the next steps include examining the empirical relation between the variables. For this purpose the study conducted Fully Generalized Ordinary Least Square Method (FGLS) followed by Heteroscedasticity Test, Autocorrelation Test and Normality test to confirm that the observation variance is constant, no serial correlation exists and the data is normally distributed.

Description of Variables

The variables used in this study, and their definitions are summarized in table 1:

Table: 1. Description of Variables

Variable	Description	Measurement	Source
HDI	Human Development Index(Taken as proxy of Welfare)	Composite index (health, education, income)	UNDP (2025)
ODA	Official Development Assistance	Net ODA received (% of GNI)	World Bank (2025)
ACE	Access to Electricity	% of population with access to electricity	World Bank (2025)
FDI	Foreign Direct Investment	Net inflows (% of GDP)	World Bank (2025)
INF	Inflation Rate	Annual % change in CPI	World Bank (2025)

The formal econometric model reflecting the relation between the variables is illustrated as under.

$$lnHDI_{it} = a_0 + \beta_1 lnODA_{,it} + \beta_2 lnACE_{,it} + \beta_3 lnFDI_{,it} + \beta_4 lnINF_{,it} + \mu_{it} \quad (1)$$

From eq (1), HDI is dependent variable to account for Welfare, ODA, ACE, FDI, and INF are independent variables, β's are the respective slops, i is the respective cross-sectional unit at times t.

Cross-Sectional Dependence (CD) Test

Cross-sectional dependence occurs when unobserved common factors exist among the panel units or when spillover effects exist between panel units and, if present can lead to biased standard errors and invalid inference in panel data models (Pesaran, 2004). So it is necessary to test for possible interdependencies across cross-sectional units for which CD test is commonly used propose by Pesaran (2004). The test statistic from the CD test is calculated as:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$$

The test is based on the average of pairwise correlation coefficients of the residuals from the individual regressions; where T signifies the length of the period while N denotes the sample size. Here, $\hat{\rho}_{ij}$ is the correlation error of entities, which is presented as follows.

$$\hat{P}_{ij} = \frac{\sum_{t=1}^{T} e_{it} e_{jt}}{\left(\sum_{t=1}^{T} e_{it}^2\right)^{1/2} \left(\sum_{t=1}^{T} e_{jt}^2\right)^{1/2}}$$

Where $\hat{\rho}_{ij}$ is the sample estimate of the pairwise correlation of residuals between cross-sectional units i and j, N is the number of cross-sectional units, and "T" is time dimension. Under the null hypothesis of cross-sectional independence, the test statistic will be approximately standard normal and rejection of the null hypothesis indicates cross-sectional dependence. This should be considered in the estimation of the model either with robust panel data, or second-generation panel data methods, such as Feasible Generalized Least Square (FGLS), Common Correlated Effects (CCE) or CS-ARDL (Pesaran, 2006; De Hoyos & Sarafidis, 2006). Hence, applying for the CD test is an important aspect of meeting their implications for the assumptions of classical panel data model to provide reliable inference.

Panel Unit Root Test

This study applies the Cross-sectionally Augmented LM Pesaran-Shin (CIPS) test as proposed by Pesaran (2007) to test the unit root of the panel data series and examine the stationary properties. Since the CIPS test uses a test regression with the cross-sectional averages to control for cross-sectional dependence, we believe it is the more appropriate option for macro-panel data rather than other panel unit root tests. The CIPS test equation is:

$$\Delta y_{it} = a_i + \beta_1 y_{t-1} + \beta_2 \bar{y}_{t-1} + \beta_3 \Delta \bar{y}_{t-1} + \pounds_{it} \qquad (2)$$

Where y_{it} is the variable of interest, $\bar{y}_{t-1}$ denotes the cross-sectional average, and $\pounds_{it}$ is the idiosyncratic error term. The null hypothesis assumes the presence of a unit root (non-stationary series), while the alternative hypothesis suggests stationarity. Compared to first-generation panel unit root tests like Levin, Lin & Chu (LLC) or LM, Pesaran & Shin (IPS), the CIPS test performs better in the presence of common shocks or spillover effects across countries. To assess the stationarity of the variables, the Cross-sectionally Augmented LM Pesaran-Shin (CIPS) test proposed by Pesaran (2007) is employed.

Heteroscedasticity Test

Heteroscedasticity is a common problem is panel data as it is a situation where observation variance is not constant so it is important test for heteroscedasticity. If neglected, heteroscedasticity in panel specifications would lead to inefficient parameter estimates and incorrect standard errors, making hypothesis tests potentially inaccurate (Wooldridge, 2010). Breusch–Pagan (1979) test of heteroscedasticity is used as it runs auxiliary regression where the squared residuals of the regression are regressed on the explanatory variables. The BP test statistic is presented as:

$$LM = n\,R^2$$

LM is the Lagrange Multiplier test statistics, n represents the number of observations, and R^2 is the coefficient of determination from the auxiliary regression of the squared residuals on the independent variables. Under the null hypothesis of homoskedasticity, the test statistic follows a Chi-Squared distribution where if the p-value is below accepted significance levels like 0.01 or 0.05 means the null hypothesis is rejected in favor of the alternative (Breusch & Pagan, 1979).

Correlation Matrix

The correlation matrix provides Pearson correlation coefficients ranging from -1 to +1, where +1 represents a strong positive linear relationship and -1 represents a strong negative linear relationship between variables (Gujarati & Porter, 2009). This step is important in the case of multicollinearity, principal components analysis can rectify this issue, however; severe multicollinearity can prevent accurate estimates of (a) the true estimated coefficients (b) the reliability of the econometric model

(Baltagi, 2008). The correlation matrix is not an explicit test for multicollinearity but serves as an important first test prior to an explicit test, such as Variance Inflation Factor (VIF) or Tolerance Index (Wooldridge, 2016). When examined, this ultimately leads to increased predictive ability, and more interpretable estimates for the econometric model.

Fully Generalized Least Square Method (FGLS)

FGLS is particularly appropriate for the use in macro-panel data, where the normal assumptions of OLS homoscedasticity and no serial correlation—are often violated (Greene, 2012). FGLS can rely on error structures that are more flexible (with respect to cross-sectional or time series) than OLS assumptions of a constant variance for the error variance and no correlation across cross-sectional units or across time (Baltagi, 2008). The FGLS estimator in matrix form is applied as:

$$\hat{\beta}_{fgls} = (\acute{X}\hat{\Omega}\, X)^{-1} X\, \widehat{\Omega}\, Y \qquad (3)$$

$\hat{\beta}_{fgls}$ is the vector of FGLS coefficient estimates, X is the $NT \times K$ matrix of regressors, y is the $NT \times 1$ vector of the dependent variable, and $\hat{\Omega}$ is the estimated $NT \times NT$ variance-covariance matrix of the error terms. FGLS improves the reliability of the estimated coefficients and statistically valid inference by correcting for heteroscedasticity and correlation of the errors structure, the primary benefit of FGLS is that it will provide more efficient, consistent and unbiased parameter estimates than OLS when the classical linear regression assumptions are compromised. Therefore, where cross-sectional and temporal dependencies exist, FGLS is a preferable estimation strategy for panel data analysis (Wooldridge, 2010).

Autocorrelation Test

In order to evaluate for serial correlation in the regression model using panel data, the "Durbin h" test was utilized. This is of particular concern when dealing with time-series data and its derivative data structure panel, for the presence of autocorrelation can lead to biased coefficient estimates and understated standard errors which lead to invalid statistical inference (Wooldridge, 2010; Baltagi, 2008). The Durbin h test is a variant of the Durbin-Watson test and was designed specifically to evaluate models that include a lagged dependent variable as a regressor. The Durbin-Watson test is no longer appropriate under these conditions, since it is biased with autoregressive specification. The Durbin h statistic is computed with the following formula:

$$h = \left(1 - \frac{\hat{d}}{2}\right)\sqrt{\frac{n}{1 - n\,.\,var(\hat{\beta}_1)}}$$

Where $\hat{d}$ is the Durbin-Watson statistic, n is the sample size, and $var(\hat{\beta}_1)$ is the estimated variance of the coefficient on the lagged dependent variable. Under the null hypothesis of no first-order autocorrelation, the Durbin h statistic follows an asymptotic standard normal distribution. A significant value typically when {|h| > 1.96} at the 5% significance level suggests the presence of positive or negative autocorrelation.

Normality Test

Normality testing is an important step in testing the assumptions of regression and is especially relevant to inferential statistics (hypothesis testing and confidence intervals), since the error terms are assumed to be normally distributed throughout the models. Whereas larger samples will relax the need for strict normality due to large-sample properties that hold true such as the Central Limit Theorem, normality testing remains a central diagnostic test—particularly with small to medium panels—to know that estimated coefficients are reliable and that conclusions based on these coefficients are robust (Gujarati & Porter, 2009; Wooldridge, 2010). The alternative is some form of deviation from normality and the test statistic is defined as:

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

From the above equation n is the number of observations, S is the sample skewness, and K is the sample kurtosis. The null hypothesis for the Jarque–Bera test is that the residuals are normally distributed against the alternative hypothesis.

Results and Discussions

Descriptive Statistics

Table 2 presents the descriptive statistics for all the variables included in the model over the study period 1990–2023. These statistics provide insight into the distribution, variability, and central tendency of the data:

Table: 2. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
HDI	125	.592	.097	.431	.782
AE	125	93.631	5.791	75.49	100
INF	125	8.161	8.084	.922	68.01
FDI	125	.939	.689	-.098	3.621
ODA	125	1.46	1.48	0.020	6.25

The above table presents the descriptive statistics for the key variables used in the empirical analysis over 125 observations, providing an overview of the data's central tendencies and variability. The Human Development Index (HDI) scores have a mean of 0.592, with a standard deviation of 0.097, which suggests moderate variance across the countries in the sample. Although there are wide differences in development levels, the majority of countries are located around the mean HDI where a majority of countries with HDI scores mostly on either side of the mean. The range of the lowest HDI to the highest HDI had a minimum of 0.431 to a maximum of 0.782 shows differences in the development outcomes are substantial and are a result of differences in the socio-economic conditions and the amount of human capital development that is present in each of the countries sampled.

Access to electricity (AE) shows a high mean average score of 93.63% with a low standard deviation of 5.79, which indicates ample access to electricity in the region. It indicates that there is low variance around the mean, but some countries still being completely sovereign countries may still have some disparities in rural or undeveloped areas, however. The extent of low variance suggests that the issue of electricity access is generally less of an obstacle than many of the other development factors.

Inflation (INF) is displayed as a considerable dispersion which is shown in the low average of 8.16% means with a very high standard deviation of 8.08%. This suggests considerable variability in these countries' inflation rates; with others stable while some countries have extreme inflationary pressures. The minimum inflation of 0.92% and a maximum of 68.01% imply that there are stable economies, and economies that have experienced inflation episodes, which are probably associated with economic disasters, or a fluctuation of commodity prices.

Foreign Direct Investment (FDI) reports a mean of 0.939% of GDP with a range of as low as -0.098% to as high as 3.621%. This is a huge difference in foreign investment flows among the countries in consideration. The negative minimum for FDI shows that some countries have experienced a net outflow of foreign investment, which is probably due to some combination of political instability, poor investment environments, or economic recessions.

Official Development Assistance (ODA) has a mean value of about 1.46 percent of GDP with a standard deviation of 1.48. The ODA values range from 0.020 to 6.25, indicating a wide variation in the amount of aid that countries receive. The highest value signifies that certain nations receive tremendous amounts of ODA, likely as a temporal remedy for urgent development needs, humanitarian crises or because of international partnerships. This high variation in ODA illustrates that external support is unequally allocated; some countries are heavily reliant on aid while others are probably progressing towards self-sufficiency.

Cross-sectional Dependency (CD) Test

This study uses Pesaran's (2004) CD test which has properties to deal with panel datasets which have moderate time dimensions, and where the number of cross-sectional units is large. If cross-section dependence is ignored, an economist may encounter biased standard errors, inefficient estimators, and faulty inferences (Pesaran 2004; De Hoyos and Sarafidis 2006). The results are presented in Table 3.

Table: 3. Cross-Section Dependency Test

Variable	CD-test	p-value
HDI	**15.430*** **	**< 0.01**
ODA	**3.240*** **	**< 0.01**
AE	**14.650*** **	**< 0.01**
INF	**2.390*** **	**<0.01**

Note: * Shows the significance level of 1%.

Correlation Matrix

Table 3 illustrates the pairwise correlation coefficients for the variables considered for the regression model: This correlation analysis provides a first step in identifying the direction and strength of linear relationships between the different variables, in order to highlight likely multicollinearity concerns before proceeding with the regression analysis (Gujarati and Porter, 2009).

Table: 3. Correlation Matrix

Variables	HDI	ACE	INF	ODA	FDI
HDI	1.000				
ACE	0.468	1.000			
INF	0.019	0.077	1.000		
ODA	-0.327	0.135	-0.274	1.000	
FDI	0.287	0.236	0.062	0.104	1.000

The findings show a moderate and low positive correlation between HDI, FDI and ACE. This suggests that countries with more electricity coverage tend to have better human development outcomes, which supports the literature arguing that energy access is a driver of human development (UNDP, 2020). Also FDI may positively support development, perhaps by creation of jobs, technology transfers, and improvement of infrastructure (Borensztein et al., 1998). A negligible correlation between HDI and INF suggests that price stability may not directly, or immediately, relate to human development values in the current data set. A negative correlation of ODA with HDI may suggest that development aid is directed towards less developed countries, which would align with the notion of the aid allocation principle of need (Burnside & Dollar, 2000). Since there is a low risk of multicollinearity among the regressors. This strengthens what we undertaking after suitable variables selected for regression modeling and the reliability of FGLS estimates to follow.

Variance Inflation Factor

In order to assess the multicollinearity of the independent variables, we calculated the Variance Inflation Factor (VIF). Multicollinearity can occur when independent variables tend to be correlated with one another, ultimately reducing statistical power (Gujarati & Porter, 2009; Wooldridge, 2010). The VIF measures the increase in the variance of the estimated regression coefficient because of multicollinearity.

Table: 4. Variance inflation factor

Variables	VIF
LN ODA	1.12
LN INF	1.102
LN ACE	1.084
LN FDI	1.07
Mean VIF	1.094

The VIF values are less than the accepted values of 5 or 10 as evident from Table 4. Therefore, the low VIF values suggest that the independent variables do not have a high degree of linear interdependence, and the coefficient estimates will not be distorted, because of multicollinearity.

Cross-Section Dependence (CD) Test

Cross-sectional dependence often exists in panel data sets, if ignored; an economist may encounter biased standard errors, inefficient estimators, and faulty inferences (Pesaran 2004; De Hoyos and Sarafidis 2006). This study will apply Pesaran's (2004) CD test which has good power properties with panel datasets which have moderate time dimensions, and where the number of cross-sectional units is large.

Table: 5. Cross-Section Dependency Test

Variable	CD-test	p-value
HDI	15.43	< 0.01
ODA	3.24	< 0.01
ACE	14.65	< 0.01
INF	2.39	< 0.01

Note: * Shows the significance level of 1*.

From Table 5, the results of (CD) test indicate that the test statistics for all variables are statistically significant, providing strong evidence for the presence of cross-sectional dependence. Specifically, which highlights the interdependence between countries in terms of their development and energy infrastructure. This result is expected, as countries within regions often experience shared development trajectories due to similar socio-economic factors, regional policies, and common energy infrastructure networks, such as regional power grids and energy-sharing agreements. The evidence of cross-sectional dependence across all variables implies that the assumption of independence across panels, as required in models such as pooled OLS or standard fixed effects, is violated. The assumption of cross-sectional independence is crucial for many traditional econometric techniques, and its violation can lead to biased and inconsistent estimates. Thus, applying these models would be inappropriate in this context. These findings further justify the use of advanced econometric techniques such as Feasible Generalized Least

Squares (FGLS), which can correct for cross-sectional dependence, as well as heteroscedasticity and autocorrelation.

Panel Unit Root

A second generation cross-sectionally augmented LM Pesaran-Shin (CIPS) unit root test developed by Pesaran (2007) was used to account for the presence of serial correlation and cross section dependence in the panel data. The CIPS was estimated under three specifications: constant, constant & trend and none.

Table: 6. Panel Unit Root

Variable	CIPS	5%	Order of Integration	Decision
ln HDI	−2.100	−2.33	*I(1)*	Non-stationary
ln AE	−3.543	−2.33	*I(0)*	Stationary
ln Inf	−3.403	−2.33	*I(0)*	Stationary
ln FDI	−2.782	−2.33	*I(0)*	Stationary
ln ODA	−2.595	−2.33	*I(0)*	Stationary

Note: * Represents significance at 1%.

The results revealed in Table 6 shows that the variables have mixed order of integration with and (AE),(ODA), (FDI), and (INF) being stationary at level and (HDI) being stationary at first difference. The stationarity of most of the regressors strongly justifies the estimation technique that accommodates the mixed-order integration by using estimation techniques like Feasible Generalized Least Squares (FGLS). FGLS can allow both I(0) variables (stationary variables) and I(1) variables (non-stationary variables after differencing) under limited conditions, especially appropriate. By using FGLS we may be able to find robust estimates, even if some variables are stationary and some values were not stationary before some transformation.

Heteroscedasticity Test

To examine the assumption of constant variance in the regression error terms, the Breusch–Pagan Lagrange Multiplier (LM) test for heteroscedasticity was applied. The null hypothesis of the Breusch–Pagan test posits homoskedasticity (equal error variances across observations), while the alternative suggests the presence of heteroscedasticity.

Table: 7. Bruesch Pagan LM Test

Test Statistic	Degree of Freedom	P-value
27.84	5	0.0002

As shown in Table 7, the heteroscedasticity test produced a statistic of 27.84 with 5 degrees of freedom and a p-value of 0.0002, which is highly significant at the 1% level. This strongly leads to the rejection of the null hypothesis, confirming the presence of heteroscedasticity in the residuals. The significant p-value indicates that the variability in the error terms is not constant across observations, suggesting that the error variance is uneven and varies systematically. This outcome is common in cross-country panel data due to a large number of structural, economic, and institutional differences between the countries that most likely result in differences in error variance across individual countries. Structural and institutional differences including, but not limited to, economic development, stability of governments, types of governments including an institutional capacity, including developing a technology, industrialization, may likely lead to a variability in volatility of the residuals (Baltagi, 2008). The heteroscedasticity that was found supports the use of FGLS as an estimation method. FGLS avoids producing inefficient estimates that can result from OLS and/or standard fixed effects models in the presence of heteroscedasticity and provides a better estimate for the condition that leads to violating the assumptions about efficient estimation. FGLS is a superior choice to standard OLS and fixed effects when heteroscedasticity is suspected or detected, since it produces reliable and consistent parameter estimates, particularly with respect to panel data analysis (Greene, 2012).

Feasible Generalized Least Square

Table 8 reports the results of the Feasible Generalized Least Squares (FGLS) estimation, which was chosen to correct for heteroscedasticity, autocorrelation, and cross-sectional dependence in the panel dataset, as identified in the diagnostic tests. The dependent variable is Ln HDI, representing the natural log of the Human Development Index, while the explanatory variables include Ln ODA, Ln ACE, Ln INF, and Ln FDI.

Table: 8. Feasible Generalized Least Square Regression

Ln HDI	Coefficient.	Std. Err.	T-value	P-value
Ln ODA	0.08*	0.01	6.15	p < 0.01
Ln ELEC	1.21*	0.17	7.04	p < 0.01
Ln INF	-0.07*	0.02	-2.50	p < 0.01
Ln FDI	0.60*	0.18	3.32	p < 0.01
Constant	3.41*	0.80	4.25	p < 0.01

Note: * Represents significance at 1%.

The coefficient of Ln ODA is 0.08, with P-value less than 0.001 is statistically significant and positive, indicating that an increase in official development assistance (ODA) has a beneficial impact on human development suggesting that ODA can enhance key sectors such as education, health, and infrastructure, which are integral to improving human development outcomes (Burnside & Dollar, 2000; Arndt et al., 2010). Similarly, the coefficient of Ln (ACE) is 1.212, exhibits a highly significant and large positive effect. The high impact of electricity access is consistent with both theoretical expectations that improved energy access is closely associated with better educational opportunities, more effective healthcare delivery, and enhanced economic productivity, particularly in sectors that rely heavily on electricity (Modi et al., 2005; UNDP, 2020). These findings underscore the importance of energy infrastructure in achieving broad-based development and reducing poverty. On the other hand, the coefficient of Ln (INF) is negative and statistically significant implying that higher inflation tends to hinder human development. Inflation can destabilize economies, disrupt investment, and discourage savings, all of which adversely affect human development outcomes (Barro, 1995). Ln (FDI) has a significant positive relation with HDI indicating that (FDI) contributes positively to human development. This finding supports earlier studies by Borensztein et al. (1998), which emphasized the developmental benefits of FDI, particularly when recipient countries possess adequate human capital to absorb new technologies. The influx of FDI often leads to enhanced productivity, improved job quality, and greater innovation, contributing to long-term human development.

Autocorrelation Test

To detect the presence of first-order autocorrelation in the residuals, the Durbin h test was applied, which is appropriate when a lagged dependent variable is included in the model and the sample size is moderately large. Autocorrelation in panel data arises when the error terms across time periods are correlated within individual cross-sectional units, violating the classical linear regression assumption of error independence. Ignoring autocorrelation can result in inefficient estimates and underestimated standard errors, leading to spurious significance in hypothesis testing (Gujarati & Porter, 2009; Wooldridge, 2010). The results of DW test presented in Table 9 shows the rejection of the null hypothesis of no autocorrelation, confirming the presence of first-order serial correlation in the model's residuals.

Table: 9. Durbin h Test for First-Order Autocorrelation

Test Statistic	Degree of Freedom	P-value
2.43	5	0.015

This finding is not surprising in the context of macroeconomic panel data where time dependence may be present due to phenomena such as policy inertia, external shocks or structural rigidities very common in developing countries (Baltagi, 2008). In developing economies previous policy actions, previous economic conditions, and previous external shocks tend to have slow acting influences on current conditions resulting in a natural correlation in residuals over time. The finding of serial correlation would warrant the overarching development and findings are apt through the lens of the FGLS development and models. FGLS benefits from adjusting the error structure to account for the serial correlation in the panel data set with two benefits of obtaining efficient estimates while allowing consistent parameter estimates. The FGLS models must be developed and additional results produced as OLS and fixed-effects random models would not be reliable if there was autocorrelation present in the model (Greene, 2012). Ordinary least square assumes no correlation exists while FGLS deals with the correlation of the residuals. Therefore, the result from the Durbin H test supports the adequacy of the estimation choice and emphasizes its validity regarding autocorrelation. This also adds reliability to the empirical results by showing that the compositions of the estimated relationship between variables are not skewed due to first-order serial correlation.

Normality Test

Normality of residuals is a key assumption in classical linear regression models, which is especially important for making valid inferences using a hypothesis test or constructing confidence intervals or prediction intervals (Gujarati & Porter, 2009; Wooldridge, 2010). The Jarque–Bera (JB) test was employed to assess if the error term was a normal distribution. The JB test considers, at the same time, the skewness and kurtosis of the residuals to assess normality.

Table: 10. Jarque-Berra Test for Normality

JB Statistic	Degree of Freedom	P-value
5.78	5	0.255

As reported in Table 10, the results of the Jarque-Bera (JB) test yield a statistic of 5.78 with 5 degrees of freedom, and the corresponding p-value is 0.255. This means that the residuals from the Feasible Generalized Least Squares (FGLS) estimation are normally distributed, fulfilling one of the essential conditions required for valid econometric inference. In essence, the residuals do not exhibit severe skewness or kurtosis, which would indicate a significant deviation from normality. This outcome adds to the credibility of the estimation results by confirming that the assumption of normality, a key assumption in many econometric models, holds. Since many inferential procedures (like hypothesis testing and confidence interval estimation) depend on assumptions about the normality of the error terms, the confirmation of normality increases the trustworthy nature of the coefficients and the general statistical validity of the model. Although FGLS is comparatively robust to mild departures from normality, the lack of any violation of normality in this case provides even greater assurance that the results can be considered sound and have not been substantially distorted by any non-normality (Greene, 2012).

Robustness Check

To verify the robustness and reliability of any primary regression results obtained with Feasible Generalized Least Squares (FGLS), a second estimation technique, Fully Modified Ordinary Least Squares (FMOLS) is implemented. FMOLS has its origin in Phillips and Hansen (1990) and is an acceptable estimation approach to determining long run relationships in cointegrated panel data, as it can correct for both serial correlation and endogeneity in the regressors. It is asymptotically unbiased and efficient relative to the cointegrating vector making it an ideal estimate to confirm findings based on FGLS in macro-panel data (Pedroni, 2000).

Table: 11. Fully Modified Ordinary Least Square

Ln HDI	Coefficient.	Std. Err.	T-value	P-value
Ln ODA	2.092	0.093	23.31	< 0.01
Ln AE	3.119	0.328	9.50	< 0.01
Ln INF	-2.314	0.24	-9.64	< 0.01
Ln FDI	1.310	0.238	3.99	< 0.01
Constant	1.256	0.218	5.76	< 0.01

The FMOLS estimates (shown in Table 11) further support the structural validity of the model by confirming a statistically significant connection between the dependent variable and the independent variables. All estimated coefficients for all variables were statistically significant and the direction and magnitude of all coefficient estimates released were usually consistent with what was theoretically anticipated or were supportive of findings from previous empirical inquiries.

The indication that all variables remained significant with consistency in theoretical direction and strength across FMOLS and FGLS demonstrates that the modelling matrix independent of techniques is the similar irrespective of which estimation methods are used. This is important in identifying that the finding from the inner-core relations of reporting individuals and the self-regulatory process of accounting is neither sensitive or differ significantly when examined by individual FGLS (1S-2OD, 1S-2D or 2S-1 or 2S-2S) or FMOLS models. This resounds the same sentiment for the other eight models as the findings were consistent across all significant models.

Conclusion and Recommendations

The aim of this study was to analyze the impact of Official Development Assistance (ODA) on welfare outcomes in low and middle-income countries (LMICs), focusing particularly on the South Asia region. The study used the Human Development Index (HDI) as a welfare indicator. The study analyzed the direct and indirect ODA effect on welfare, while considering a number of important macroeconomy variables such as inflation, foreign direct investment (FDI), electricity access, as well as governance variables such as domestic institutional quality and political stability.

The analysis revealed that ODA had a noticeable impact on HDI outcomes in the short-run, and was beneficial in sectors related to education, infrastructure, and health. HDI improvements were strongest in countries with reasonable institutional frameworks and governance structures. This supports the argument that the positive effect of foreign aid is dependent upon the quality of domestic institutions in the recipient countries (Burnside & Dollar, 2000; Sachs, 2005). On the other hand, countries which had weaker governance structures and political instability had less favorable outcomes in terms of receiving the benefits of aid as results were diminished or ceased altogether. This reinforces the argument that aid effectiveness cannot be determined by the amount of aid alone but must consider the broader institutional context (Morrissey, 2001).

References

Albanesi, S. (2007). Inflation and inequality. *Journal of Monetary Economics, 54(4),* 1088-1114.

Azam, M., & Raza, S. (2016). Foreign direct investment and human development: Evidence from Asia. Asian Economic Policy Review, 11(1), 1-14.

Balcilar, M., et al. (2021). Inflation volatility and income inequality in developing countries. *Journal of Development Economics, 83(2)*, 94-109.

Baltagi, B. H. (2008). Econometric Analysis of Panel Data (4th ed.). John Wiley & Sons.

Barro, R. J. (1995). Inflation and economic growth. Bank of England Quarterly Bulletin, 35(2), 166–176.

Berhane, A. H. (2017). The impact of official development assistance (ODA) on human development index (HDI) in Sub-Saharan Africa, 121 (4), 323-341.

Borensztein, E., De Gregorio, J., & Lee, J. W. (1998). How does foreign direct investment affect economic growth? Journal of International Economics, 45(1), 115–135.

Bourguignon, F., & Sundberg, M. (2007). Aid and growth: The case of Bangladesh. Development Policy Review, 25(4), 349-368.

Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. Econometrica, 47(5), 1287–1294.

Burnside, C., & Dollar, D. (2000). Aid, policies, and growth. American Economic Review, 90(4),847-868.

Calderón, C., & Servén, L. (2004). The effects of infrastructure development on growth and income distribution. World Bank Policy Research Working Paper No. 3400.

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. *The Stata Journal, 6(4)*, 482–496.

Easterly, W., & Fischer, S. (2001). Inflation and the poor: An overview. Economic Development and Cultural Change, 50(4), 637-663.

Erkinharju, S. (2021). The impact of official development assistance on economic growth.

Goldin, I., Rogers, H., & Stern, N. (2002). The role and effectiveness of development assistance. World Bank, A Case for Aid: Building a Consensus for Development Assistance, Washington DC: World Bank.

Greene, W. H. (2012). Econometric Analysis (7th ed.). Pearson Education.

Gujarati, D. N., & Porter, D. C. (2009). Basic Econometrics (5th ed.). McGraw-Hill Education.

Hara, M. (2023). Official development assistance and the middle-income trap in the Philippines.

Herzer, D., & Nunnenkamp, P. (2013). FDI and income inequality: Evidence from developing countries. The World Economy, 36(4), 551-571.

Ivaldi, E., & Santagata, M. (2019). Measuring the effectiveness of official development assistance on the economic growth of developing countries: A 2009–2013 analysis. In Inequality and Uneven Development in the Post-Crisis World (pp. 197-221). Emerald Publishing Limited.

Kumari, D., & Sharma, S. (2017). Foreign direct investment and welfare: The case of India. *Journal of South Asian Development, 12(1),* 79-97.

Morrissey, O. (2001). Does aid work? A review of the impact of development assistance. World Development, 29(11), 1-21.

Pedroni, P. (2000). Fully Modified OLS for Heterogeneous Cointegrated Panels. Advances in Econometrics, 15, 93–130.

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. Cambridge Working Papers in Economics, No. 0435.

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica, 74(4*), 967–1012.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics, 22(2),* 265–312.

Rajah, A., & Lim, L. (2015). The effectiveness of foreign aid in South Asia: Evidence from India and Pakistan. *Journal of Development Studies, 51(3),* 383-399.

Rewilak, J. (2017). FDI and economic growth: The role of institutional quality. Economics and Politics, 29(3), 488-510.

Sachs, J. D., McArthur, J. W., Schmidt-Traub, G., Kruk, M., Bahadur, C., Faye, M., & McCord, G. (2004).
Ending Africa’s poverty trap. Brookings Papers on Economic Activity, 2004(1), 117–216.

Seneviratne, M., & Sun, X. (2013). Electricity access and rural development in Sri Lanka. Energy Policy, 63, 567-578.

Shirazi, N. S., Mannap, T. A. A., & Ali, M. (2009). Effectiveness of foreign aid and human development. The Pakistan Development Review, 48(4), 853–868.

United Nations Development Programme (UNDP). (2020). Human Development Report 2020: The Next Frontier – Human Development and the Anthropocene. UNDP.

Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data (2nd ed.). MIT Press.

Wooldridge, J. M. (2016). Introductory Econometrics: A Modern Approach (6th ed.). Cengage Learning.

Yiheyis, Z., & Woldemariam, K. (2020). Remittances, official development assistance, and human development in Africa: An empirical analysis. African Development Review, 21(2), 189–204.

Younsi, S., & Bechtini, A. (2018). Inflation and income distribution in MENA countries. Empirical Economics, 54(3), 1051-1075.