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Econometric Features of Models Used in Aid Allocation Studies

Swedish aid allocation - a comparison between a multiple linear regression, Heckman's two step model and the Tobit model

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Abstract

Research of aid allocation deals with a dependent variable, received aid expressed in absolute or relative terms, that is equal to zero for numerous observations. This is because donor countries tend to target specific countries for their allocation, leaving the rest of the countries without any development assistance. The special characteristic requires non-linear methods with censoring, truncation or selection bias of the data.

Using a panel covering Swedish aid recipient countries between 1998-2016, three commonly used models in aid allocation are examined; a multiple linear regression on a truncated data set, Heckman's two step model and the Tobit model. The models are estimated with a set of political and altruistic variables that are frequently used as explanatory factors to aid allocation, with share of Swedish aid as dependent variable.

With around 13 % of the total observations below threshold, the models yield similar parameter estimations. The results from Heckman's two step model and the multiple linear regression are almost, but not exactly, the same. This can partly be explained by the information each model has of the dependent variable, and partly by a small selection bias.

In general, the parameters have approximately the same impact on the dependent variable. However, the estimations in the Tobit model are slightly different from the other models. Countries in sub-Saharan Africa, the educational level and the expected lifespan in the recipient country have a significant effect on the share of Swedish aid received according to the Tobit model, but not in the other models. This is mainly explained by the different estimation methods in the models.

Contents

1 Introduction

The question about the efficiency of foreign aid and how it can impact economic and social progress is an ongoing debate within the field development. Studies of aid allocation has shown that there are both political strategies and altruistic interests when donor countries allocate their aid (see e.g. Alesina & Dollar, 2000; Canavire-Bacarreza, Nunnenkamp, Thiele & Triveño, 2005; Martínez-Zarzoso, Nowak-Lehmann, Parra & Klasen, 2014). In the literature, a few of the variables described as altruistic are recipient countries' level of democracy, openness and standard of living (see e.g. Dollar & Levin, 2006), while strategic factors may be the donor country's exports to the recipient country (Martinez-Zarsoso et al, 2014) or the geopolitical interest of the strategic location of a recipient country (Balla & Reinhardt, 2008). The strategic dimension has been further investigated by researchers such as Fleck and Kilby (2006), Goldstein and Moss (2007) and Sohn and Yoo (2015) by studying the differences between legislatures and how the political interest might change depending on what political party is in power.

There are some common econometric features for data and methods used in studies of aid allocation. Firstly, the dependent variable (expressed as aid in absolute or relative terms) is equal to zero for a lot of observations (e.g. Balla & Reinhart, 2008; Tarp, Bach, Hansen & Baunsgaard, 1999; Canavire-Bacarreza et al., 2005). This is because donor countries tend to target specific countries for their allocation, leaving the rest of the countries without any development assistance. Secondly, the dependent variable is often expressed in terms of a one- or two-year lag, based on the assumption that aid decisions are not taken on the ground of direct information (e.g. Berthélemy & Tichit, 2003; Neumayer, 2003; Cingranelli & Pasquarello, 1985). Thirdly, the data is either structured as a cross section with several donor and recipient countries or a panel, with one donor over a certain time period (e.g. Sohn & Yoo 2015; Canavire-Bacarreza et al., 2005). The first characteristic, that is, a dependent variable equal to zero, demands a non-linear method with censoring, truncation or selection bias of the data (Greene, 2003).

Studies utilize a range of methods to deal with the special characteristics of aid allocation; Ordinary Least Square Estimations (Goldstein & Moss, 2005) with time dummies and fixed or random individual-effects (e.g Schudel, 2008), Error Correction Models (Greene & Licht, 2017), Two Part Model Estimation (Cingranelli & Pasquarello, 1985) and Heckman's two step model (Tarp et al., 1999) to mention a few. Out of these methods, the Tobit model together with the multiple linear regression with truncation and Heckman's two step model are some of the most frequently used (Berthélemy & Tichit, 2003). Using a panel covering all the countries that received Swedish aid at least once between 1998-2016, the aim of this study is to compare the econometric properties and estimation methods of these three models.

In the linear regression model, a regression is fitted to the observations with a positive outcome for the dependent variable. This method is used by some of the pioneers in the field of human rights practices and aid distribution, Cingranelli and Pasquarello (1985), who focus on US aid to Latin American countries. They find that human rights practices do affect the US decision to provide or not provide aid, and the amount of the assistance to Latin American countries. A similar study is later employed by Neumayer (2003), who investigate the relationship between the human rights level in recipient country and the amount of received aid and find that the relationship is rather insignificant. The author use a panel covering the period 1984-1995 and smooth annual fluctuations by summarizing three year averages within the factors, and apply a one year lag between dependent and independent variable. Using a linear regression, Neumayer (2003) argues that fixed- and random-effects can be employed, thereby controlling for bias that can arise due to unobserved heterogeneity. Similar arguments for the linear regression can be found in Furuoka (2005), who examine how human rights affect aid flows from Japan. The author highlights the problem with selection bias, but justifies it by stating that it only occurs one year out of the entire examined period.

Balla and Reinhart (2008) argue that a multiple linear regression is inappropriate in their study of how conflicts affect donor's decisions on aid allocation. According to the authors, the allocation of aid is unlikely to be random. They argue that the results will be biased if there is a correlation between a donor's decision to provide aid or not and the level of aid provided. Instead, they sort their panel data in two steps; first they code the dependent variable into a binary one, where 1 equals a positive aid flow that year and 0 no received aid and apply a probit model. Next, they fit Heckman's selection model, with donor's gross aid per capita (in recipient country) as dependent variables. Based on the probit estimation, Heckman's lambda is included as an explanatory variable in the second regression to avoid potential problems with dependent error terms. This model is also used by e.g. Tarp et al. (1999) in their study of Danish Bilateral aid and Fariss (2010), who investigates US foreign food aid relation to the level of human rights in a recipient country. Common for the studies which utilize Heckman's model, is the use of robust standards errors to control for heteroskedasticity and a lagged dependent variable.

Canavire-Bacarreza et al. (2005), perform a Tobit analysis on their panel data from 1999-2002 and find that export to recipient country is one of the factors that explain aid flows. They argue that it is the best model, since Heckman's two step model risk a correlation between the error terms in the two different regressions, and further could lead to multicollinearity problems if the same variables are used in the two regressions. Based on a similar argumentation, Sohn and Yoo (2015) apply the Tobit model on their panel and find that aid policies do not differ between conservative and progressive South Korean governments. The Tobit model is also used by Berthélemy and Tichit (2002) when analyzing donor behavior on a panel with 22 donors and 137 recipient, covering the period 1980-1999. Their results imply that donors are biased towards trade partners and that political governance affect the aid flows. The authors also compare the Tobit model with a probit and OLS estimation with a truncation of the data, which generates slightly different results.

In a previous study, we investigated what explanatory factors affect the proportion of Swedish aid a partner country receives, and whether they change with governments (Lindelöw & Ågren, 2018). Using the Tobit model on a panel over all the countries that sometime received Swedish aid between 1998-2016, our empirical results suggest that there is a small difference between governments. Although the variables in general have a similar impact on the level of aid received, independent of governments, there are a few exceptions. Countries in sub-Saharan Africa and factors such as the recipient country's level of human rights and Foreign Direct Investment (FDI) have a significant effect when right wing governments are in power. However, these variables do not show any significant effects on aid distribution for left wing governments.

Our previous work encouraged an interest in how methods with a dependent variable that require censuring or truncation differ with their respective strengths and limitations. The literature on aid allocation present a range of different methods, revealing the complexity of different approaches to the field of study. In the foregoing study, we were interested in the actual variables and the impact they had on Swedish aid allocation. This present study takes an econometric approach, where the main focus is on model validation and the estimation methods, rather than the political and economic effects of aid allocation. Based on the theoretical framework presented in Lindelöw and Ågren (2018), the aim of this particular study is to compare the econometric properties and the parameter estimations of the Tobit model, a multiple linear regression with truncated data and the Heckman's two step model.

2 Research Design

The panel consists of all the countries that have received Swedish Official Development Assistance at least once during the examined time period (1998-2016) and a number of factors that are interesting from an economic and political perspective. Below follows a short description of the balanced panel and characteristics of the factors (for a more detailed description and motivation behind the use of the variables, see Lindelöw & Ågren, 2018).

2.1 Dependent variable

The dependent variable is Swedish aid, expressed as Official Development Assistance (ODA) to all sectors and partner countries from Sweden, measured in current prices (US dollars). To see the relative amount of aid a country receives, it is re-calculated to share of Swedish aid. Aid is measured as the net value of ODA as percentage of GDI, and countries that pay off debts to a higher value than received aid, show a negative value for ODA (OECD, 2018). Countries that did not receive any ODA a specific year, show a value equal to zero. Since the share of aid given to each recipient country is small, the variable is expressed in percentage. The variable will be used in its logarithm form in further analysis.

2.2 Explanatory Variables

Based on previous literature and the common goals for Swedish aid policy, we developed a framework (Lindelöw & Ågren, 2018) and divided the variables into three parts; political strategic interests, altruistic motives and control variables. ODA as % of GDP was included as a political strategic variable, to see whether or not Swedish aid flows depend on how other donor countries distribute aid. The variables sub-Saharan Africa and Europe was included to reflect geopolitical interests. As the aim of our previous study was to see whether left- and right-wing governments differ in their aid allocation, Foreign Direct Investment (FDI) was therefore included as a proxy for an economic policy traditionally promoted by right wing governments, whereas the Gini coefficient was representative for left wing governments. However, this particular study will not investigate the difference between governments in aid allocation, but rather how different methods explain the factors behind Swedish aid allocation. FDI can be seen as a proxy for a recipient country's economic openness, while Gini represents the economic inequality in the country. Some of the common goals for Swedish aid policy are reflected in the altruistic framework; sustainable environmental development (Natrent), human rights (FH) and improved living conditions (HDI). Finally, population and GDP per capita are included as control variables.

Table 1: Explanatory Variables

Variable	Description
Natrent	Total natural resources rents (% of GDP). A measure from the World Bank, calculated as the summarized profit of a natural resource (oil, gas, carbon, forest and minerals) as a part of GDP in recipient country
GDP	Gross domestic product per capita in recipient country, in constant local currency.
Pop	Population, measured in thousands (in recipient country)
FH	An index where 0 represent an unfree society, partly free equals 1 and a free country 2. Based on values from Freedom House (2016)
ODA	Total received Official Development Assistance as % of GNI in recipient country.
FDI	Foreign Direct Investments as % of GDP in recipient country
Europe	Dummy variable for countries situated in Europe
SubSah	Dummy variable for countries in sub-Saharan Africa
Gini	A measure of income equality in recipient country. 0 equals perfect equality and 1 perfect inequality (Solt, 2016)
HDI	Human Development Index. A measure of wealth in human development that consist of three key factors: educational level, expected lifespan and economic wealth (UN, 2018). Proxy for living conditions in recipient country.

2.3 Descriptive Statistics

The descriptive statistics are fairly straightforward, however there are some noteworthy values. The panel consists of 2053 observations in total, where approximately 13 % of the observations are censored or truncated in further analysis, due to a value equal to or below 0 for the dependent variable (below threshold).

Some remarkable values are the minimum values for ODA and FDI, which have a negative sign. The negative values for ODA have the same explanation as the corresponding values for the dependent variable; countries that repay debt at a higher value than the aid received show a negative value for ODA (in percent of GNI). If a foreign investment is withdrawn and is greater than the recent capital invested in the country, FDI (as percent of GDP) can be negative (UN, 2017). GDP per capita and Population show high mean values in comparison to the other factors and the dependent variable with its maximum value of 16%. These factors will be used in their logarithm form in further analysis, since they show a non-linear dependency with the dependent variable.

Due to lack of observations, the variables Gini and HDI have been interpolated linearly. That is, the progression in these variables has been filled in for the missing observations in accordance with the observed linear relation between the years that do have observations. Sensitivity tests of the interpolation can be found in Lindelöw and Ågren (2018).

Table 2: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Above threshold					
Swedish Aid	1,782	0.821510	1.448	0.000586	16.145086
Natrent	1,782	9.12334	11.065	0.00133	69.72660
GDP	1,782	2,548.229	2,896.817	102.645	16,881.210
Pop	1,782	52,620,000	179,715,256	70,630	1,371,000,000
FH	1,782	0.9624	0.743	0	2
ODA	1,782	6.5219	10.782	−0.6754	192.0260
FDI	1,782	4.382	6.644	−16.589	89.476
SubSah	1,782	0.369	0.483	0	1
Europe	1,782	0.065	0.246	0	1
Gini	1,782	0.4115	0.072	0.2290	0.6163
HDI	1,782	0.5748	0.139	0.2515	0.8470
Below threshold					
Swedish Aid	271	−0.0008391	0.006	−0.0640683	0.00000
Natrent	271	7.96508	13.505	0.00468	82.52953
GDP	271	3,805.768	3,360.299	197.316	16,737.900
Pop	271	3,755,837	11,073,339	69,670	90,728,900
FH 0.1.2	271	1.236	0.757	0	2
ODA	271	7.559	9.677	−2.629	68.572
FDI	271	6.174	6.356	−2.152	54.062
SubSah	271	0.262	0.441	0	1
Europe	271	0.01107	0.105	0	1
Gini	271	0.4282	0.067	0.2290	0.6100
HDI	271	0.6109	0.113	0.3030	0.8430

3 Description of Models

Three different models with similar econometric properties have been used in previous studies (Berthélemy & Tichit, 2003) . In this section, the models and a few basic econometric concepts are described in order to facilitate the understanding of the different methods.

3.1 The General Model

The general model can be described as:

$$Y_{it} = \beta_0 + \beta_1 X_{it-1} + \varepsilon_{it} \tag{1}$$

where Y_{it} is the share of Swedish aid the country i receives at time t, X_{it-1} is a vector of political strategical, altruistic and control variables for country i at time *t-1*, and ε_{it} is an error term. As in previous literature, the explanatory factors have a one year lag. This is due to the assumption that decisions on aid allocation are based on the past year's factor levels.

3.2 Truncation or Censoring

Since it is desirable to censor or truncate the dependent variable, a non-linear method of estimation has to be implemented. In short, the censored values in a certain range are reported as a single value, while truncated values are not even included in the analysis (Greene, 2003). Truncation of data is a type of sample bias, meaning that countries that did not receive Swedish aid in a specific year, do not even make the sample.

Truncated dependent variable:

$$Y_{it} = \begin{cases} \text{not in sample} & \text{if } Y_{it}^* \leq 0 \\ Y_{it}^* & \text{if } Y_{it}^* > 0 \end{cases}$$

Censored dependent variable:

$$Y_{it} = \begin{cases} 0 & \text{if } Y_{it}^* \leq 0 \\ Y_{it}^* & \text{if } Y_{it}^* > 0 \end{cases}$$

where Y_{it}^* is the latent variable and Y_{it} the observed result.

Censoring on the other hand, is a shortcoming in the sampled data, since non-censoring would give representative information about the population (Greene, 2003). In other words, with a censored variable, one can use the sample to estimate the probability that the observations have complete data. This is not possible with a truncation (Heckman, 1976). When censoring values at zero, negative values are shifted up to zero and the mean is therefore slightly higher than in the true population. Truncation on the other hand, increases the mean even more, since values equal to or below zero are entirely removed from the analysis (Cameron & Trivedi, 2005).

3.3 Multiple Linear Regression

There are two main regressions of interest in studies of aid allocation; whether or not a country receives aid and the level of aid received. This is sometimes referred to as the gate-keeping stage and the level-setting stage (Neumayer, 2003; Cingranelli & Pasquarello, 1985). If the field of interest was to see what factors drives the decision to provide or not provide aid to a country, a data set containing all countries in the world is desirable. In this study, the panel is delimited to the countries that did receive Swedish aid at least once during the time period 1998-2016, and a gate-keeping stage regression would therefore be misleading. Instead, the regression of interest is the level-setting stage. With a panel of all aid-receiving countries, the question is rather what the explanatory factors are to the level of aid received. That is, why do some countries receive more aid than others?

In the level-setting stage, a multiple linear regression is fitted to the observations with values above 0 (Gujarati, 2003), that is, a truncation of the data. If the first step, the gate-keeping stage, is not performed, but only the observations with positive outcome are regressed on, the parameters of an OLS estimations will be asymptotically biased (Gujarati, 2003). When the observations that show a value below or equal to zero are omitted, it is a selection bias since the positive outcomes are not necessarily independent of the negative/zero outcomes (Berthélemy & Tichit, 2002). Consequently, the expected value of the error terms may not be equal to zero, implying biased estimates (Gujarati, 2003).

The strength of this method is, however, the possibility to observe time- and individual-specific effects. Individual country-effects bias the estimates in a Tobit model (Berthélemy & Tichit 2003) and are not applicable in the Heckman's estimation (Toomet & Henningsen, 2008). Using panel data, auto correlation and heterogeneity problems may arise in a linear regression (Sohn and Yoo, 2015). A Breusch-Pagan test is conducted to see whether the data is of homoscedastic or heteroscedastic character, while the country-specific effects are tested through the Hausman test (Wooldridge, 2013). The results indicate that fixed effects are desirable for both countries and years. This implies that the individual- and time-specific effects are correlated with the explanatory variables in the model (Wooldridge, 2010). When including these specific effects in the model, it allows for periodical fluctuations of Swedish ODA and the historical relations with partner countries. This should result in an improvement of heterogeneity problems in the panel (Furuoka, 2005). The individual country-specific effects eliminates the changes that affect the level of Swedish aid on country level. Time-fixed effects accounts for the variation in the model explained by a specific year. The fixed effects on country- and time-level yield a "within-estimator", which accounts for the variation within countries over time. If there is no within transformation, the correlation of the explanatory factors would bias the estimation (Neumayer, 2003). Nevertheless, the within transformation can lead to a reduced precision of the estimations if the variation is greater across countries than over time (Allison, 2009). Variables with little or no time variation are estimated inefficiently (Neumayer, 2003).

Including individual- and time-fixed effects in the general equation (1) generates the following equation:

$$Y_{it} = \gamma_i + \delta_t + \beta_1 X_{it-1} + \varepsilon_{it} \tag{2}$$

where γ_i represent the recipient country $i's$ specific effects and is an unknown intercept for each country. It and accounts for the heterogeneity of countries that is not captured by the independent variables. δ_t is the time-specific effects year t, which allows for aggregate year effects that affect the recipient countries (Neumayer, 2003). Using fixed effects, influences that may have lead to deviations from the general aid lows can be accounted for (Claessens, Cassimons & Van Campenhout, 2009)

The expected value of the dependent variable will be conditional:

$$E[Y_{it}|Y_{it}^* > 0] = \beta_1 E[X_{it-1}|Y_{it}^* > 0] + E[\varepsilon_{it}|Y_{it}^* > 0] \tag{3}$$

As shown by the expected value of the error term, $E[\varepsilon_{it}|Y_{it}^* > 0]$, a bias term arises with the conditional expectation (Berthélemy & Tichit, 2003).

3.4 Heckman's Two Step Model

The gate-keeping and level-setting stage are both included in Heckman's two step model, where the probability of receiving aid is estimated with the probit model.

To control for sample selection bias and endogenity, this method induces a term called the inverse Mills ratio (from the probit estimation) into the explanatory factors in the second estimation, where the level is set (Berthélemy & Tichit, 2003). The inverse Mills ratio can be seen as a bias term, which arises due to the non-randomness of the observation selection in the probit estimation (Fariss, 2010). To produce consistent estimates, the mean in the first step is normalized to zero in the Heckman's model (Heckman 1976). This allows a correlation between the error terms in the different steps, and thereby consistency.

Heckman-type selection models are often used with a different set of explanatory variables in the two stages, or with at least one more explanatory factor in the gate-keeping stage (Sartori, 2003). The selection state:

$$Y_{(1)it} = \begin{cases} 0 & \text{if } Y^*_{(1)it} \leq 0 \\ 1 & \text{if } Y^*_{(1)it} > 0 \end{cases}$$

where

$$Y^*_{(1)it} = \alpha_0 + \alpha_1 X_{(1)it-1} + \varepsilon_{(1)it} \tag{4}$$

Based on a set of variables, $Y^*_{(1)it}$ observes whether the dependent variable is above zero or not (Cameron & Trivedi, 2005). That is, $Y_{(1)it}$ takes the value 1 if a country received a positive amount of aid, and 0 if no aid or a negative amount of aid was received.

The level-setting stage can be notated as:

$$Y_{(2)it} = \begin{cases} - & \text{if } Y^*_{(1)it} \leq 0 \\ Y^*_{(2)it} & \text{if } Y^*_{(1)it} > 0 \end{cases}$$

where

$$Y^*_{(2)it} = \beta_0 + \beta_1 X_{(2)it-1} + \varepsilon_{(2)it} \tag{5}$$

$Y_{(2)it}$ measures the share of aid a country received, given that it did receive a positive share of aid (Cameron & Trivedi, 2005).

$$\begin{pmatrix} \varepsilon_{(1)it} \\ \varepsilon_{(2)it} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & \sigma^2 \end{pmatrix}\right]$$

$\varepsilon_{(1)}$ and $\varepsilon_{(2)}$ are assumed to be jointly normally distributed and independent from the explanatory variables (Toomet & Henningsen, 2008). The gate-keeping equation (4), estimated with probit, normalizes $\sigma^2_{\varepsilon(1)}$ to 1, since only whether or not $Y^*_{(1)it}$ is above zero is observed (Toomet & Henningsen, 2008; Cameron & Trivedi, 2005).

Considering the aim of this study, to compare the different methods, it is desirable to use the same set of factors in both steps, as in the Tobit estimation. In addition, the same set of variables should influence all levels of decision making; both which countries should receive aid and the level of aid received. Sartori (2003) addresses the issue with the inclusion of an extra exogenous variable that does not necessarily exist, which leads to a specification error in the ρ and thereby the parameters. The author argues that Heckman-type selection models can be estimated without the additional variable, if the distributional assumption of the residuals are taken into consideration, rather than the variation in the independent variables. Against this background, the same set of variables will be used in both equations. The expected value of the level-setting stage can be defined as (Cameron & Trivedi, 2005):

$$E[Y_{(2)it}|Y^*_{(1)it} > 0] = \beta_1 X_{(2)it-1} + \rho\lambda(\beta_1 X_{(1)it-1}) \tag{6}$$

where ρ is the correlation between the error terms in the two different stages and λ is the inverse Mill's ratio. If ρ is equal to zero, there is no sample selection bias. For a more detailed description of the mathematical theory, see e.g. Heckman (1976) and Cameron and Trivedi (2005).

Heckman's selection model does not support fixed individual effects, however, time-fixed effects can be included in the model. The method augments the OLS regression by an estimate of the omitted regressor $\rho\lambda(\beta_1 X_{(1)it-1})$ (Cameron & Trivedi, 2005).

Heckman's two step model or Heckman's selection model is the name used in aid literature. However, the model is sometimes called a probit selection equation (Wooldridge, 2013), a bivariate sample selection model, the Heckit estimation (Cameron & Trivedi, 2005) or the type 2 Tobit model (Amemiya, 1984). The last name of the model, the type 2 Tobit model, reveals its similarities with the Tobit model.

3.5 The Tobit Model

This model is popular among economists and is similar to Heckman's method, although $Y^*_{(1)it} = Y^*_{(2)it}$ in the Tobit model (Cameron and Trivedi, 2005). That is, the two steps in Heckman's selection model is just one in the Tobit model:

$$Y^*_{it} = \beta_0 + \beta_1 X_{it-1} + \varepsilon_{it} \tag{7}$$

where

$$\varepsilon_{it}|\mathrm{X}_{it-1} \quad \sim \quad N\left(\ 0, \sigma^2\ \right)$$

The Tobit model measures the latent dependent variable, while in Heckman's model, the latent variable is included as an independent variable (Cameron & Trivedi, 2005). Another difference between how the two methods are applied in this study, is the estimation method. Heckman's method uses ordinary least squares, while the Tobit model augments the maximum-likelihood estimation (Tobin, 1958; Cameron & Trivedi, 2005).

$$Y_{it} = max(0, Y^*_{it})$$

The method manages to estimate consistent parameters through the maximum-likelihood method, although the dependent variable comes with restrictions (Tobin, 1958). However, the model relies heavily on the assumptions of normal distributed and homoskedastic error terms, as brought up in Cameron & Trivedi (2005). The authors further argue that if these assumptions are not met, the MLE is inconsistent. The expected value of the level of aid received is described as (Wooldridge, 2013):

$$E[Y_{it}|Y_{it}^* > 0] = \beta_1 X_{it-1} + \sigma\lambda \tag{8}$$

where the inverse Mills' ratio $\lambda = \lambda(\beta_1 X_{it-1}/\sigma)$ depends on the standardized magnitude of $\beta_1 X_{it-1}$ and σ is the standard deviation of ε_{it}. In our previous study (Lindelöw & Ågren, 2018), this was the model used for the analysis. However, the heavy reliance on the assumptions and the interpretation of the parameters is problematic. The linear effect of X_{it-1} on Y_{it} is not β_1, and the effect is therefore not on the observed result (for a detailed explanation, see McDonald & Moffitt, 1980). Another downside with this model is that individual-specific country effects can not be included, however, there is no problem with time specific effects. In a model with fixed effects, the slope of the parameters can be estimated consistently (Henningsen, 2010).

4 Estimation Methods

Based on the methodology described above, four models, all with time-fixed effects, are estimated; a multiple linear regression on the truncated data set (1a), a multiple linear regression also including country-specific effects (1b), Heckman's two step model (2) and a Tobit model (3).

4.1 Approaches to Parameter Estimations

One of the main differences between the different models is the parameter estimation. The multiple linear regression and Heckman's method augments the ordinary least square (OLS), while the Tobit model augments the maximum-likelihood estimation (MLE). In short, OLS minimizes the squared distance between the observed value in the dataset and the predicted values with a linear approximation, i.e the residuals (Wooldridge, 2013). MLE, on the other hand, maximizes the likelihood function, or the log-likelihood function, and chooses the parameter value that have the largest likelihood for the observed values (Wooldridge, 2013).

4.2 Multicollinearity

Multicollinearity is a common problem in econometric studies. When one explanatory factor in a multiple regression is linearly predicted by one or more of the other explanatory factors, this variable might not be significant in the predicted model although it is a valid individual predictor (Wooldridge, 2013). The variable HDI is an index partly calculated with GNI per capita, which in turn has a close linear relationship with GDP per capita (HDR, 2018). Multicollinearity between the variables makes it problematic to run HDI and GDP per capita in the same regression. Since GDP per capita is a control variable in the regression, and HDI one of the altruistic variables of interest in the study, both variables are of importance in the regression.

The Variance inflation factor (VIF) reflects factors that have an impact on the uncertainty of the coefficient estimates and is often used to detect multicollinearity (Wooldridge, 2013). Running a linear regression model on the truncated data set, results in relatively high VIF values for HDI and GDP per capita (VIF values can be found in appendix). Therefore, a linear regression with GDP per capita as an explanatory factor to HDI is fitted, which indicates that 75% of the variation in HDI is explained by the variation in GDP per capita. To remove this effect in the main models of the study, the residuals of this regression replaces HDI as an explanatory factor. In other words, the effect of a recipient country's HDI on the level of Swedish aid received, is only the effect of expected years of schooling and life expectancy, not the economic part of the index.

4.3 AIC

The Akaike information criterion (AIC) is used for statistical inference to measure the quality of the linear models. The estimator calculates the information loss in a model and weights the simplicity and the goodness-of-fit of the model against each other (Cameron & Trivedi, 2005). With a logarithmic outcome variable, an extra modification of the AIC is necessary (Akaike, 1978). Using the dependent variable in its logarithmic form improves the criterion sharply, and log (Swedish aid) is therfor used in further analysis. Unfortunately, AIC has conditions not convenient with the multiple linear regression with individual-specific effects or the Heckman's estimation. However, it can be defined for the multiple linear regression with time-fixed effects and the Tobit model.

4.4 Variable inclusion

Based on previous literature and theory, a set of explanatory variables is selected. Nevertheless, these set of variables might not be relevant to the predictive power the model. To determine what variables to include in the analysis, a stepwise selection of the variables is conducted.

Stepwise selection of the independent variables is helpful for the trade off between a complete, informative model and the precision of estimation (Draper & Smith, 1981). The variable selection is conducted on the linear regression model with truncated data and time-fixed effects. Backward elimination is not supported when also including individual-specific effects in the model. The results of the stepwise selection is an elimination of the dummy variable for countries in sub-Saharan Africa and GDP per capita. GDP per capita is eliminated due to its multicollinearity with HDI. However, when the economic effect of HDI is removed, GDP per capita remains among the selected variables. Since removing the dummy variable for countries in sub-Saharan Africa have a barely noticeable effect on the AIC and R^2, and is a factor of interest, it is kept for further analysis.

In our previous study, Government Efficiency, Gender Development Index (GDI), Swedish Exports and West Asia were included in the analysis (Lindelöw & Ågren, 2018) . These variables contributes to an unbalanced panel with their lack of observations, which in turn generates estimation problems in the censored regressions. Although it would be interesting to investigate these variables, the weight of this study is on the different models rather than the actual variables and they are therefore excluded in favor of the estimation methods.

4.5 Goodness-of-Fit

Wooldridge (2013) describe the coefficient of determination R^2, as a measure of how well the variation in the dependent variable can be explained by the independent variables in the model. In the case of this study, R^2 measures how well the variation in the share of Swedish aid a country receives that can be explained by the variables included in the different models. The adjusted R^2 adjusts for the number of parameters estimated in the model (Wooldridge, 2013). However, the coefficient of determination is not measurable in the Tobit model.

4.6 Coefficient Presentation

Standardization of coefficient is a way to compare the relative importance of each coefficient in each model, where the variable with the highest absolute value has the strongest effect on the dependent variable (Draper & Smith, 1981). However, since both the dependent variable and two of the explanatory factors (GDP per capita and population) are logarithmic, the interpretation of standardized coefficients could be confusing. That is, one percentage increase in a logarithmic variable change the expected share of Swedish aid by β_i percent, while a change in a non-logarithmic variable by one (unit) would change the dependent variable by 100 x β_i percent. Since the aim of the study is to compare the estimated coefficients between the models rather than the relative importance of each variable within each model, the regression results are presented without standardized coefficients.

5 Results

The results from the different estimation methods are presented in Table 3. The first model is a multiple linear regression model estimated with time-fixed effects (1a), and next, the same model is estimated with an inclusion of country-specific effects (1b). Model two and three represent Heckman's two step model and the Tobit model, respectively, with time-fixed effects but without country-specific effects. The first models (1a and b) are based on the truncated data set with 1782 observations, while the other two models use the full data set with 2053, and censor the 271 observations where the dependent variable is equal to or below zero.

Including country-specific effects does not have a big impact on the other estimated coefficients. The parameters and the standard deviations are approximately the same for the OLS model (1a) and the model with country-specific effects (1b). Although the inclusion of country-specific effects should improve heterogeneity problems, it does not seem to change the parameter estimations. Common for all models is the kind of impact (positive or negative) each variable has on the share of Swedish aid a country receives. Countries with a high level of natural resources and GDP per capita receives a significant smaller part of Swedish aid, ceteris paribus. This is also true for countries who have a high level of freedom, according to the index from Freedom House.

The variables with a significant positive impact on the level of aid received, according to all the estimation methods, is the population, ODA as % of GDI, FDI as % of GDP and countries in Europe. In other words, the bigger the population, the more Swedish aid the country receives. The same applies for ODA and FDI, the bigger share of ODA and FDI that accounts for a country's economy, the more aid is received from Sweden. Countries in Europe receive more aid from Sweden in comparison to countries outside of Europe. These results are of course similar to the findings in Lindelöw and Ågren (2018).

However, the results of interest are the similarities and differences of the parameter estimations between the models. Countries south of the Sahara and the non-economic part of HDI only seem to have a big significant positive effect in the Tobit model, not in any of the other models. The effect of these variables are also the ones that differs the most among the variables in the different models, probably due to their lack of significance.

What is noticeable, is that the multiple linear regression without individual-specific effects yields almost the same estimates as Heckman's selection model. In addition, the coefficient of determination (R^2) and the adjusted R^2 is the same for the two models. When including individual-specific effects in the multiple linear regression (1b) the R^2 increases, however the adjusted R^2 decreases, due to the increased number of parameters estimated (countries and years). The AIC is only computed for the first model and the Tobit model, and suggest that the Tobit model has a better trade off between the simplicity and the goodness of fit than the linear model.

Focusing on Heckman's model and more specifically the inverse Mills ratio and the correlation term between the errors in the gate-keeping and level-setting state regressions, neither of them are statistically proven to be different from zero. This explains why the estimated parameters are so close to the OLS estimation. If either of the terms is equal to zero, the expected value of received share of Swedish aid is equal between the multiple linear regression and Heckman's model.

Table 3: Regression Results

	Dependent variable:Log (Swedish aid)			
	Linear with time-fixed effects (1a)	*Linear with country and time-fixed effects* (1b)	*Heckman's model* (2)	*Tobit regression* (3)
Intercept	-9.718^{***}		-9.718^{***}	
	(0.850)		(1.0792)	
Natrent	-0.021^{***}	-0.022^{***}	-0.021^{***}	-0.026^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
logGDP	-0.569^{***}	-0.628^{***}	-0.570^{***}	-0.538^{***}
	(0.061)	(0.065)	(0.061)	(0.079)
logPop	0.568^{***}	0.562^{***}	0.568^{***}	1.100^{***}
	(0.032)	(0.033)	(0.049)	(0.034)
FH	-0.326^{***}	-0.277^{***}	-0.325^{***}	-0.279^{***}
	(0.067)	(0.070)	(0.067)	(0.088)
ODA	0.037^{***}	0.037^{***}	0.037^{***}	0.043^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
FDI	0.017^{**}	0.021^{***}	0.017^{**}	0.021^{**}
	(0.007)	(0.008)	(0.007)	(0.010)
SubSah	0.176	0.080	0.177	1.082^{***}
	(0.151)	(0.155)	(0.159)	(0.166)
Europe	2.741^{***}	2.577^{***}	2.742^{***}	3.753^{***}
	(0.209)	(0.216)	(0.221)	(0.366)
Gini	6.582^{***}	6.670^{***}	6.583^{***}	7.499^{***}
	(0.730)	(0.754)	(0.728)	(0.895)
HDIres	0.298	0.452	0.301	5.356^{***}
	(0.939)	(0.975)	(0.965)	(1.092)
Observations	1,782	1,782	2,053	2,053
R^2	0.308	0.314	0.308	
Adjusted R^2	0.298	0.255	0.298	
Akaike Inf. Crit.	711.871			-2149.30
ρ			0.003	
Inverse Mills Ratio			0.005	
			(0.332)	

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

6 Discussion

The aim of the study was to investigate how the econometric features and the estimated parameters differ between Heckman's model, a multiple linear regression with truncated data and the Tobit model. Using a panel covering all the countries that received Swedish ODA at least once between 1998-2016, the results imply that there is almost no difference between a time-fixed multiple linear regression with truncated data and Heckman's model with time-fixed effects. The estimated parameters from the Tobit model are similar to the results from the other models; however, countries in sub-Saharan Africa and the non-economic part of HDI only yield significant parameters in the Tobit model.

The main explanation for the similarity between the multiple linear regression (1a) and Heckman's model (2), both estimated with time-fixed effects, is that the correlation between the two error terms in Heckman's model cannot be proven to be different from zero and neither the inverse Mills ratio. The inverse Mills ratio has a relatively high standard deviation, indicating that the coefficient might be zero. Furthermore, the correlation between the two error terms, ρ, do not show any standard deviation at all. This is one of the limitations of the study. Since ρ is the correlation between the error terms in the gate-keeping and level-setting stage in the Heckman's model, it relies heavily on the specifications of the model. In this study, the same set of variables is used for both stages, altering the normal set up for the model. Although an extra exogenous factor usually is included in the second step (equation 5), the same set of explanatory factors are assumed to influence whether or not a country receives aid and the level of aid received. If ρ or the inverse Mills ratio (or both) are equal to zero, equation 6 becomes equation 3.

The results from the two models are almost, but not exactly, the same. This indicates that the impact of either one or both terms on the regression is small. These findings cast some doubt on Heckman's model on this particular data set, and moreover, approves the use of linear regression with a truncated data set. Although there is selection bias, the linear regression is as useful as Heckman's model, but with simpler econometric properties. This further validates the argumentation that can be found in Neumayer (2003) and Furuoka (2005).

The results in Berthélemy and Tichit (2003) are similar to the results of this study. They use the Tobit model for their main analysis, and test for the two step method as an alternative method. First they estimate the probit model (the first step in Heckman's model), which in general estimate similar parameters as the Tobit model, although there are two exceptions. Two of the parameters in their regression (FDI and ODA) change sign. The authors also control for a truncated multiple linear regression, which generate even more different parameters. They argue that this is due to the selection bias.

In general, the parameter estimations are more even in this study, since all estimations show the same sign in the different methods. Furthermore, the results between the multiple linear regression and Heckman's model are strikingly similar. This might be due to the nature of the selection bias. The data set does not consist of all the countries in the world, but only those which received Swedish aid at least once between 1998-2016. Therefore, the selection bias is small in comparison to e.g. the bias in Berthélemy and Tichit (2003), who have a rich data set with 22 donors and 137 recipients, covering 20 years.

However, the estimated parameters in Heckman's two step model and the multiple linear regression are not exactly the same. This is partly explained by the different information the models have of the dependent variable. Heckman's model censor zero and negative values, thereby treating them as unobserved. The multiple linear regression on the other hand, is preformed on the truncated data set, thereby not including any information of these observations in the regression.

Using the "within" transformation (model 1b) to perform inference allows for a consistent and unbiased estimation of the OLS model (Wooldridge, 2013). Even though it would be desirable to include country-specific effects in the Tobit model, the assumptions are approximately met (appendix residuals) and the MLE is therefore consistent. In addition, the inclusion of country-specific effects does not change the estimated parameters much, and neither the determination coefficient. This implies that although the Hausman test suggested individual-specific effects, it is not of great importance on the final result. In other words, the non-availability of applying the country-specific effects in the Heckman's model or the Tobit model does not affect the inference remarkably. An F-test for individual-specific effects support these findings.

In sum, the Tobit model differs the most from the other model estimations, although the estimated parameters are similar. The main explanation is that the first three models are estimated with ordinary least squares, while the Tobit model uses the maximum-likelihood estimation. Although the MLE is more efficient, the OLS estimation is more commonly used in Heckman's model (Cameron & Trivedi, 2005). This is since it is easily implemented and do not require as strict distributional assumptions about joint normality of the error terms as the MLE (Cameron & Trivedi, 2005).

Using Heckman's model or a multiple linear regression with or without individual-specific effects barely makes any difference on the inference. These results imply that the selection bias, and thereby the bias generated from truncation, is small and the use of Heckman's model can therefore be doubted. As mentioned earlier, the AIC is only computed for the multiple linear regression and the Tobit model. However, since the multiple linear regression is so similar to the Heckman's model, the AIC for model 1a is comparable with model 2. Although it is commonly used for linear models, the criterion is sharply improved in the Tobit model, implying a more qualitative model.

7 Conclusion

Based on a panel covering information of all the countries that received Swedish aid at least once between 1998-2016, three common models used in aid allocation studies has been compared. With a dependent variable that takes a values equal to or below zero, the results yields both similarities and differences between the multiple linear regression with truncated data, Heckman's model and the Tobit model.

There are striking similarities between Heckman's model and the multiple linear regression when both estimated with time-fixed effects. This is because neither the correlation term between the two error terms in the two steps, nor the inverse Mills ratio are proven to have a significant effect in Heckman's model, indicating that the selection bias is small. Although commonly used in previous literature, the use of Heckman's model on this data is questionable, since it yields almost the same parameter estimations as the multiple linear regression with truncated data.

Although similar, the estimated parameters are not exactly the same. This can partly be explained by the information each model has of the dependent variable. Heckman's model treat zero and negative values as unobserved, while the linear regression is estimated on a truncated data set, i.e there is no information about the observations when the dependent variable is equal to or below zero.

In general, the parameter estimations in the different models are very alike. The main difference is the dummy variable for countries in sub-Saharan Africa and the part of the Human Development Index that measures educational level and life expectancy. These parameters are significant in the Tobit model, but not in the other models. Heckman's model and the linear regression both use ordinary least squares for the parameter estimation, while the Tobit model adapts the maximum-likelihood estimation. If there were to be further analysis, it would be of interest to compare a wider selection and variation of models. More specifically, a maximum-likelihood estimation of Heckman's model would fortify the results from this study.

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9 Appendix

9.1 List and Sources of Variables

Table 4: List and sources of variables

Variable	Source
Swedish Aid	OECD: https://data.oecd.org
Natrent	World Bank: https://data.worldbank.org
GDP	World Bank: https://data.worldbank.org
Pop	World Bank: https://data.worldbank.org
FH	Freedom House: https://freedomhouse.org/report-types/freedom-world
ODA	World Bank: https://data.worldbank.org
FDI	World Bank: https://data.worldbank.org
Europe	UN: http://data.un.org
SubSah	UN: http://data.un.org
Gini	Solt, Frederick. 2016. "The Standardized World Income Inequality Database." Social Science Quarterly 97(5):1267-1281. SWIID Version 6.2, March 2018.
HDI	UN: http://data.un.org

9.2 Packages used in R

The data has been structured in Microsoft Excel, and computed in R with the following packages.

Table 5: Packages used in R

dplyr	psych	car	jtools
sampleSelection	nnet	ggplot2	reshape2
censReg	ExPanDaR	lmtest	fitdistrplus
plm	readr	MASS	jtools
ggstance	stargazer	AER	

9.3 Residual Analysis

In linear regression, there are several assumptions about the inference in the model. These assumptions are normal distribution among the stochastic components, an independent distribution of error terms with the expected mean value zero and homoscedasticity (Sheather, 2009).

The scatter plots presented below (Figure 1) show the residuals from the multiple linear regression with time-fixed effects. There are two observations (720 and 818) that show a strong leverage in figure 1. These residuals represent Liberia in 2007 and 2008, which showed a high ODA in comparison to other countries these years. It is important to pay attention to these observations and how they might have an impact on the inference. However, the observations are still within ”Cook’s distance”, and are therefore not excluded from the analysis.

The Normal Q-Q plot show that the residuals are approximately normal distributed (they follow

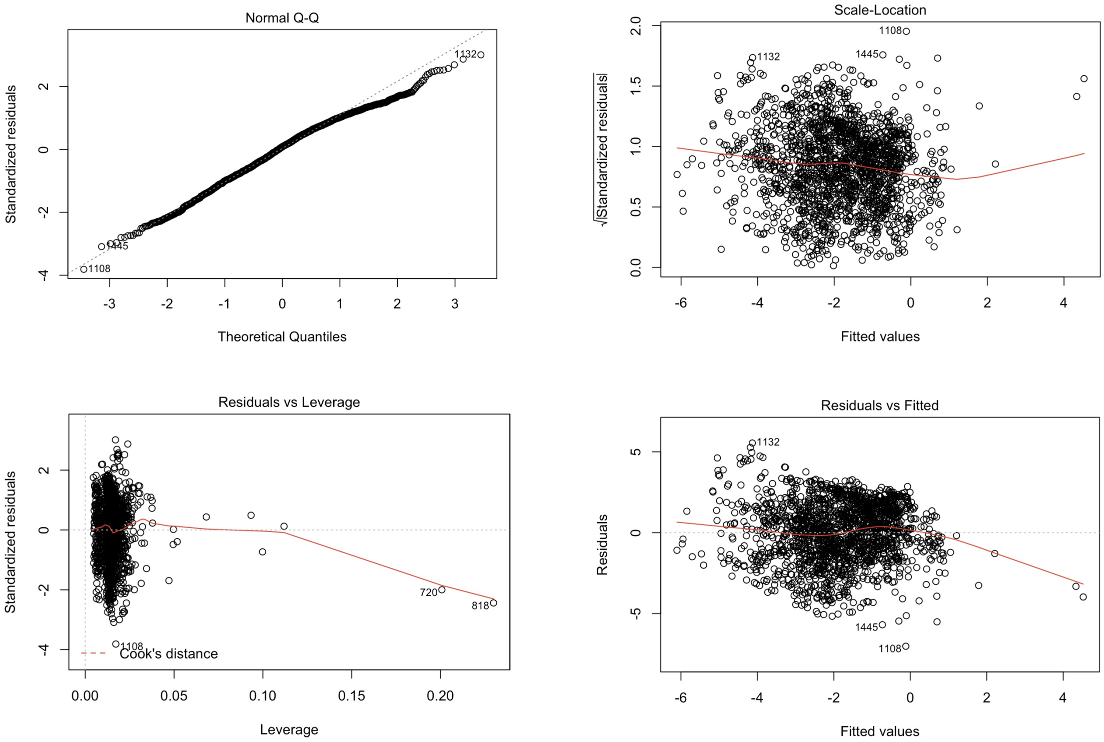

Figure 1: Residual Plots

the straight diagonal line). Although there are a few outliers, the Scale-Location Diagram show that the residuals are equally spread along the range of predictors, and above and below the line. There are two leverage points in the Residuals vs Fitted diagram, but in general, it shows a tendency of a linear relationship with the truncated data set. In sum, the assumptions for a linear model are approximately fulfilled.

9.4 Sensitivity Tests

Table 6: Sensitivity Tests

	BP test	Hausmantest	F test
H_0	Homoscedastity	No individual-specific effects	Model 2
H_1	Heteroscedasticity	Individual-specific effects	Model 1
BP/Chisq/ F	110.35	29.026	0.82881
df	10	10	114/1641
p-values	$<$ 2.2e-16	0.001234	0.9021
Result	Heteroscedasticity	Individual-specific effects	Model 1 is better

9.5 Correlation Plots

The plots vizualize Pearson correlations above the diagonal and Spearman correlations below. As can be seen, the correlation is not as strong when removing the economic part of HDI.

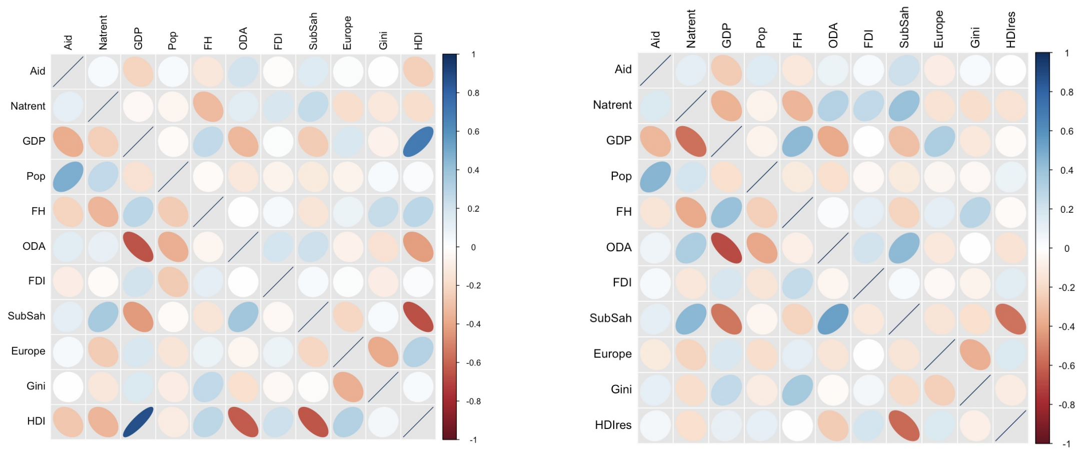

Figure 2: Correlation Plots

9.6 Variance Inflation Factor

The table present the Variance inflation factor (VIF) before and after removing the economic effect of HDI. The VIF is lowered in both logGDP and HDIres after removing the effect.

Table 7: VIF

Variable	Before	After
Natrent	1.380	1.380
logGDP	5.663	2.594
logPop	1.253	1.276
FH	1.286	1.294
ODA	1.571	1.605
FDI	1.231	1.244
SubSah	2.661	2.731
Europa	1.360	1.367
Gini	1.408	1.445
HDI/HDIres	8.570	2.107

9.7 Recipient Countries

Table 8: Countries in Sample

Afghanistan	Albania	Algeria	Angola
Argentina	Armenia	Azerbaijan	Bangladesh
Belarus	Belize	Benin	Bhutan
Bolivia	Bosnia and Herzegovina	Botswana	Brazil
Burkina Faso	Burundi	Cabo Verde	Cambodia
Cameroon	Central African Republic	Chad	Chile
China	Colombia	Comoros	Congo
Cook Islands	Costa Rica	Cote d'Ivoire	Croatia
Cuba	DPR of Korea	DR Congo	Djibouti
Dominica	Dominican Republic	Ecuador	Egypt
El Salvador	Equatorial Guinea	Eritrea	Ethiopia
Fiji	FYR of Macedonia	Gabon	Gambia
Georgia	Ghana	Grenada	Guatemala
Guinea	Guinea-Bissau	Guyana	Haiti
Honduras	India	Indonesia	Iran
Iraq	Jamaica	Jordan	Kazakhstan
Kenya	Kiribati	Korea	Kosovo
Kyrgyzstan	Laos PDR	Lebanon	Lesotho
Liberia	Libya	Madagascar	Malawi
Malaysia	Maldives	Mali	Marshall Islands
Mauritania	Mauritius	Mexico	Moldova
Mongolia	Montenegro	Morocco	Mozambique
Myanmar	Namibia	Nepal	Nicaragua
Niger	Nigeria	Pakistan	Palau
Palestina	Panama	Papua New Guinea	Paraguay
Peru	Philippines	Rwanda	Saint Lucia
Samoa	Sao Tome and Principe	Senegal	Serbia
Seychelles	Sierra Leone	Slovenia	Solomon Islands
Somalia	South Africa	South Sudan	Sri Lanka
Sudan	Suriname	Swaziland	Syrian Arab Republic
Tajikistan	Tanzania	Thailand	Timor-Leste
Togo	Tunisia	Turkey	Turkmenistan
Uganda	Ukraine	Uruguay	Uzbekistan
Vanuatu	Venezuela	Vietnam	Yemen
Zambia	Zimbabwe		