

# **Ayuda igualitaria. El impacto de la ayuda al desarrollo sobre la desigualdad en América Latina**

## **Egalitarian Aid. The Impact of Aid on Latin American Inequality**

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### **Resumen**

La literatura sobre la relación entre la ayuda y la desigualdad es escasa y ofrece resultados contradictorios. La mayoría de los estudios se basan en datos de panel estáticos o dinámicos usando efectos fijos o aleatorios para lidiar con la endogeneidad. Además de usar estas técnicas, esta comunicación introduce dos aspectos nuevos: la persistencia de la desigualdad y la naturaleza doblemente censurada del índice de Gini. Se estima un modelo de panel dinámico estimado bajo Máxima Verosimilitud Simulada a una selección de 18 países latinoamericanos en el periodo 1990-2008. Los principales hallazgos son que el gasto en consumo público, la inversión directa extranjera tuvieron un impacto positivo sobre la desigualdad mientras que la ayuda al desarrollo lo tuvo negativo (igualitario). Ni los impuestos ni el gasto público social tuvieron un efecto significativo sobre la desigualdad.

**Palabras clave:** Panel dinámico, panel doblemente censurado, desigualdad, ayuda al desarrollo, América Latina.

### **Abstract**

Literature on the relationship between aid and inequality is scarce and contradictory. Most studies are based on panel data and use fixed or random effects techniques under static or dynamic modelling to deal with endogeneity. In addition to these techniques, this article introduces the persistency of inequality and a double-censored Gini index. We apply a dynamic and double-censored panel data estimated applying the Simulated Maximum Likelihood method to a sample of 18 Latin American countries for 1990-2008. The main findings are that public expenditure in consumption and foreign direct investment had a positive effect on inequality whereas aid had a negative (egalitarian) effect. Neither taxes nor public social spending had a significant effect on inequality.

**Key words:** dynamic panel data, double censored panel data, inequality, foreign aid, Latin America.

**JEL:** C23, C24, F35.

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**Área Temática:** Desarrollo y cooperación

**Comunicación**

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## 1. INTRODUCTION

Latin America is the most unequal region in the world. Gini indexes across the continent's countries are the highest even when taxes and transfers are taken into account (Goñi, López and Servén 2011). Some institutional and historical studies have attributed this fact to colonialism, its institutional influence (Engerman and Sokolof 2002) and to natural capital and factor endowments (Acemoglu, Johnson and Robinson 2002). Recent studies have shown that Latin America was not always such an unequal region in the long run (Williamson 2009, Milanovic 2009, Prados de la Escosura 2007 a, b). Moreover, there is a generalized reduction of inequality across Latin American countries since 2002 (Gasparini & Lustig 2011; Lustig et al 2011).

The main goal of this article is to identify what variables explain inequality levels and variations in 18 Latin American countries from 1990 to 2008. Specifically, our goal is to find out whether foreign aid has had a significant effect on inequality reduction.

Although literature on the relationship between aid and growth is abundant, this is not the case for aid and inequality. Literature on aid and growth is still controversial (see McGillivray et al 2006) even when meta-analysis techniques are used. Whereas the meta-analysis of Doucouliagos and Paldam (2011) does not find any significant effect of aid on growth, Mekasha & Tarp (2011) show positive results using meta-analysis as well. There are some recent studies showing a positive link using a variety of robust econometric techniques (Dovern & Nunnenkamp 2007; Nowak-Lehmann 2009; Minoui & Reddy 2010; Arndt et al. 2010, 2011; Juselius et al. 2011 and Tezanos et al 2012 for the Latinamerican case).

The relationship between aid and inequality has been studied to a lesser extent. Bornschier et al (1978) found that aid has a positive effect on income inequality, as well as foreign investment. Dolan & Tomlin (1980) do not confirm this seminal result and find no significant correlation between aid and inequality for 1970-1973. Cuesta et al. (2006) found a negative relationship between aid and inequality using an ordered probit with annual data for 1995-98, but the effect was very sensible to sample countries and regions. In Latin America the effect was the lowest and the lower initial inequality was, the lower was the effect identified. Under the donor countries perspective, Chong & Gradstein (2008), using *World Values Surveys* data, found an inverse relationship between income inequality in the donor country and citizen agreement with foreign aid. Using cross-country regression and dynamic panel data, Chong et al (2009) found no significant effect of aid on inequality or poverty. Layton & Nielson (2008) and Bjørnskov (2010) found a positive relationship between aid and inequality in the form of a regressive effect. Both studies identified a stronger regressive effect in democratic countries but did not in autocratic. The result is partially explained by rent-seeking activities and by the fact that aid is captured by local elites. This fact is also found by Angeles and Neanidis (2010) and Holder and Raschy (2010).

Reviewing these results is interesting because it is often assumed that aid reduces poverty and that poverty can be reduced, not only through economic growth, but also by reducing inequality. If aid is pro-poor it should reach the poorest among income distribution. In fact, international summits and OECD-DAC High Level Fora have explicitly remarked inequality reduction as one of the goals behind aid<sup>1</sup>.

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<sup>1</sup> Among others, the United Nations Millennium Declaration in 2000 states that: "#2. We recognize that, in addition to our separate responsibilities to our individual societies, we have a collective responsibility to uphold the principles of human dignity, *equality* and equity at the global level"; and in "#6. We consider certain fundamental values to be essential to international relations in the twenty-first

We study income inequality under three vectors of variables: redistributive policies, human capital and labour market institutions, and external financial flows. While addressing the empirical relationship between aid and inequality, we deal with the intrinsic characteristics of inequality. In other words, we bear in mind heterogeneity and persistence of inequality, multicollinearity among regressors and endogeneity. Moreover, for the first time, a double-censored estimation technique is used (because the fitted Gini must be between the [0-100] interval) and time series are considered stationary.

This robust methodology will allow us to know if the most unequal region of the world has been positively affected by foreign aid or not. Conversely to previous literature, it also allows to know the persistence and heterogeneity among sample countries.

The structure of the article is as follows. Section 2 discusses the methodologies for a consistent estimation of inequality. Section 3 describes the data used and the statistic analysis of variables. Section 4 shows the results under different methodologies and section 5 concludes.

## 2. EMPIRICAL METHODOLOGY

Empirical studies on the relation between aid and inequality have to solve an initial problem, the size of the sample. This disadvantage does not allow obtaining consistent results. To solve this, other authors have used panel data among others econometric methodologies, i.e. the studies consider this relation simultaneously for a sample of individuals and periods. Following this formulation, we express a general model as a linear panel data:

$$EQ_{i,t} = aX_{i,t} + bY_{i,t} + gZ_{i,t} + e_{i,t}$$

$$i = 1, \dots, N \quad t = 1, \dots, T \quad (1)$$

Where  $EQ_{i,t}$  is inequality index value (Gini) in a year t and for a country i.

$X_{i,t}; Y_{i,t}; Z_{i,t}$  are regressor vectors with annual values of variables that show redistributive policies, human capital and labour market institutions and external financial flows, all of them for the same country and year as the dependent variable.

Finally,  $e_{i,t}$  is residual.

In expression (1) we are interested in the relation between aid and inequality, but there are other idiosyncratic effects (heterogeneity), known as individual effects.

There are two ways to isolate the individual characteristics of common effects:

Fixed effects, i.e. effects that are constant for all periods:

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century. These include: *Equality*. No individual and no nation must be denied the opportunity to benefit from development. The equal rights and opportunities of women and men must be assured". The Paris Declaration (OECD 2005) says: "#2. At this High-Level Forum on Aid Effectiveness, we followed up on the Declaration adopted at the High-Level Forum on Harmonisation in Rome (February 2003) and the core principles put forward at the Marrakech Roundtable on Managing for Development Results (February 2004) because we believe they will increase the impact aid has in reducing poverty and *inequality*, increasing growth, building capacity and accelerating achievement of the MDGs". Finally, the Accra Agenda for Action (OECD 2008) states: "#3. We need to achieve much more if all countries are to meet the Millennium Development Goals (MDGs). Aid is only one part of the development picture. Democracy, economic growth, social progress, and care for the environment are the prime engines of development in all countries. Addressing *inequalities* of income and opportunity within countries and between states is essential to global progress".

$$e_{i,t} = l_i + u_{i,t} \quad u_{i,t} : iid(0, s^2) \quad (2)$$

Random effects, or variables in each moment:

$$e_{i,t} = l_{i,t} + u_{i,t} \quad u_{i,t} : iid(0,1) \quad l_{i,t} : iid(0, s_i^2) \quad (3)$$

The choice depends of the correlation between each regressor and this effect, i.e. if it is null (fixed) or not (random). We use the usual Hausman test for taking a decision. If the effect is fixed, we use OLS to estimate the expression (1); but if the effects are random, the consistent estimation method is WITHIN.

Next, we have to identify if data panel is static or dynamic. A priori, as a dependent variable with lags is not a regressor, we would think of a static model. But, as the above-mentioned literature shows, there is an inverse causality relation between the dependent variable and each regressor, which leads to endogeneity.

Besides the problem of endogeneity, multicollinearity problems could arise to the relations among the regressors. To avoid these drawbacks, we proceed as follows

First, we estimate the correlation matrix of the regressors. If two regressors have a significant correlation ( $\pm 10\%$ , or higher in absolute value), we do not include them simultaneously in the model to avoid problems of multicollinearity.

Next, we estimate expression (1) with each of the isolated regressors. Then we analyze the residual to test for endogeneity, and reject the regressors for which the hypothesis of no autocorrelation is not accepted. We continue to include regressors and to test the autocorrelation of residuals, until we obtain the model with the highest goodness of fit degree, measured by  $R^2$ .

In the context of individual effects, multicollinearity and endogeneity, the consistent estimation method for a static panel data is GLS weighted by the covariance matrix of the residuals from the previous estimates WITHIN and BETWEEN [see Arellano, 2003].

If static models estimated using this procedure have autocorrelation in the residuals, we should define a dynamic model and estimate it by GMM with instrumental variables to correct the problem of endogeneity. Usually, the instrument is a delayed dependent variable, both in levels and in difference, resulting in the SYS-GMM methodology.

Existing literature already applies the methodology described above, but not to a Latin American sample. In order to overcome endogeneity, we want to analyze the persistence of inequity. We shall use a delayed dependent variable not simply as an instrumental variable, but also as a regressor.

Then, expression (1) with autoregressive is:

$$EQ_{i,t} = aX_{i,t} + bY_{i,t} + gZ_{i,t} + rEQ_{i,t-1} + e_{i,t} \\ i = 1, \dots, N \quad t = 1, \dots, T \quad (4)$$

We estimate the expression (4) by SYS-GMM AR(1), which has not been used in previous literature to study the persistence of inequality.

Another feature not considered in existing literature is that the observed dependent variable is double-censored: Gini index has lower (0) and upper (100) bounds. Then, the truncation requires a nonlinear panel data model that allows to take into account the other properties mentioned (individual effects, endogeneity, multicollinearity and autoregressive). The model is:

$$\begin{aligned}
EQ_{i,t}^* &= aX_{i,t} + bY_{i,t} + gZ_{i,t} + e_{i,t} \\
i &= 1, \dots, N \quad t = 1, \dots, T \\
EQ_{i,t}^* &= \begin{cases} 0 & \text{if } EQ_{i,t} \leq 0 \\ EQ_{i,t} & \text{if } 0 < EQ_{i,t} < 100 \\ 100 & \text{if } EQ_{i,t} \geq 100 \end{cases} \quad (5)
\end{aligned}$$

To estimate expression (5) in the presence of individual effects and endogeneity, the usual instrumental variables cannot be used [see Honoré and Hu (2004)]. Honoré and Hu (2004) study alternative techniques as GMM modified, Censored Least Absolute Deviations, Symmetrically Censored Least Squared and Maximum Likelihood. But their proposal considers that the variable is truncated only at the lower bound and, they do not include different autoregressive parameters for each individual, then, as Wooldridge (2005) indicates, the flexibility of Maximum Likelihood allows us to design the behavior of the dependent variable in greater detail.

Among the possible alternatives, Simulated Maximum Likelihood (SML) allows the use of more complex dependency structures, i.e. random effects and autoregressive different for each individual.

To implement SML, we define the log-Likelihood function for a double-censored (lower and upper bounds) model as:

$$\begin{aligned}
LL(a, b, g, W) &= \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T \left[ I_{i,t}^0 \log F \left( \frac{(aX_{i,t} + bY_{i,t} + gZ_{i,t} + e_{i,t}) - 0}{s_u} \right) \right. \\
&\quad \left. - I_{i,t}^{100} \log F \left( \frac{(aX_{i,t} + bY_{i,t} + gZ_{i,t} + e_{i,t}) - 100}{s_u} \right) \right. \\
&\quad \left. + (1 - I_{i,t}^0 - I_{i,t}^{100}) \log f \left( \frac{EQ_{i,t}^* - (aX_{i,t} + bY_{i,t} + gZ_{i,t} + e_{i,t})}{s_u} \right) \right] \log s_u \\
i &= 1, \dots, N \quad t = 1, \dots, T \\
I_{i,t}^0 &= \begin{cases} 1 & \text{if } EQ_{i,t} \leq 0 \\ 0 & \text{otherwise} \end{cases} \\
I_{i,t}^{100} &= \begin{cases} 1 & \text{if } EQ_{i,t} \geq 100 \\ 0 & \text{otherwise} \end{cases}
\end{aligned} \quad (6)$$

Where  $F$  and  $f$  are the normal accumulated distribution and density functions, respectively.

Next, we define the variance and covariance matrix structure to show autocorrelation and heterogeneity with different parameters for each individual:

$$\begin{aligned}
e &: F(0, W) \\
W &= \begin{pmatrix} W_1 & 0 & L & 0 \\ 0 & W_2 & L & 0 \\ M & M & O & M \\ 0 & 0 & L & W_N \end{pmatrix} \\
W_i &= \frac{s_u^2}{1-r_i^2} \begin{pmatrix} 1 & r_i & L & r_i^{T-1} \\ r_i & 1 & L & r_i^{T-2} \\ M & M & O & M \\ r_i^{T-1} & r_i^{T-2} & L & 1 \end{pmatrix} + s_i^2 \begin{pmatrix} 1 & L & 1 \\ 1 & L & 1 \\ M & M & M \\ 1 & L & 1 \end{pmatrix} \\
i &= 1, \dots, N \quad t = 1, \dots, T
\end{aligned} \tag{7}$$

To identify the model, we need to normalize parameters by  $s_u^2$ , so residuals have a standard normal distribution with mean zero and unit variance.

Then, we estimate SML by Geweke-Hajivassiliou-Keane (GHK) simulator [Gourieroux and Monfort (1993); Hajivassiliou, et al. (1996); Hajivassiliou and McFadden (1998); Geweke and Keane (2000)]. For that, we apply Choleski decomposition of covariance-variance matrix. But, as this is a block diagonal matrix, we can operate independently with each individual. Thus, Choleski decomposition for an individual is:

$$\begin{aligned}
W_i &= C_i g C_i^T \\
C_i &= \begin{pmatrix} c_{i,1,1} & 0 & L & 0 \\ c_{i,2,1} & c_{i,2,2} & L & 0 \\ M & M & O & M \\ c_{i,T,1} & c_{i,T,2} & L & c_{i,T,T} \end{pmatrix}
\end{aligned} \tag{8}$$

We implement GHK simulator for any individual as follows:

Generate T (number of years observed) random numbers from standard normal distribution and, we transform it as:

$$\begin{aligned}
h_i &= C_i \times x = \begin{pmatrix} c_{i,1,1} & 0 & L & 0 \\ c_{i,2,1} & c_{i,2,2} & L & 0 \\ M & M & O & M \\ c_{i,T,1} & c_{i,T,2} & L & c_{i,T,T} \end{pmatrix} \times \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \end{pmatrix} = \begin{pmatrix} h_1 \\ h_2 \\ \vdots \\ h_T \end{pmatrix} \\
x &: F(0,1) \quad h_i : F(0, C_i)
\end{aligned} \tag{9}$$

Then, for each instant, we calculate the simulated value or the value truncated, if it is higher (lower) to bounds:

$$f_{i,t} = \begin{cases} F^{-1}(u_{i,t}) \frac{aX_{i,t} + bY_{i,t} + gZ_{i,t} + \hat{a} \sum_{k=1}^{t-1} f_{i,k}}{c_{i,t,t}} & \text{if } 0 \leq EQ_{i,t} \\ EQ_{i,t} - \frac{aX_{i,t} + bY_{i,t} + gZ_{i,t} + \hat{a} \sum_{k=1}^{t-1} f_{i,k}}{c_{i,t,t}} & \text{if } 0 < EQ_{i,t} < 100 \\ F^{-1}(u_{i,t}) \frac{aX_{i,t} + bY_{i,t} + gZ_{i,t} + \hat{a} \sum_{k=1}^{t-1} f_{i,k} - 100}{c_{i,t,t}} & \text{if } EQ_{i,t} \geq 100 \end{cases}$$

$u_{i,t} : U(0,1)$  (10)

Where U is the uniform distribution.

For an instant the simulated likelihood function value is:

$$LL_{i,t} = \frac{1}{c_{i,t,t}} \left[ I_{i,t}^0 \log F \left( \frac{aX_{i,t} + bY_{i,t} + gZ_{i,t} + \hat{a} \sum_{k=1}^{t-1} f_{i,k}}{c_{i,t,t}} \right) + I_{i,t}^{100} \log F \left( \frac{aX_{i,t} + bY_{i,t} + gZ_{i,t} + \hat{a} \sum_{k=1}^{t-1} f_{i,k} - 100}{c_{i,t,t}} \right) \right] + (1 - I_{i,t}^0 - I_{i,t}^{100}) \log f \left( \frac{EQ_{i,t} - \frac{aX_{i,t} + bY_{i,t} + gZ_{i,t} + \hat{a} \sum_{k=1}^{t-1} f_{i,k}}{c_{i,t,t}}}{c_{i,t,t}} \right)$$

$I_{i,t}^0 = \begin{cases} 1 & \text{if } EQ_{i,t} \leq 0 \\ 0 & \text{otherwise} \end{cases}$   
 $I_{i,t}^{100} = \begin{cases} 1 & \text{if } EQ_{i,t} \geq 100 \\ 0 & \text{otherwise} \end{cases}$  (11)

We repeat the first three stages R times. So, for an individual, the SML mean is:

$$\bar{LL}_i = \frac{1}{R} \sum_{r=1}^R \sum_{t=1}^T LL_{i,t} \quad (12)$$

Finally, SML of panel data is:

$$LL(a, b, g, W) = \frac{1}{NT} \sum_{i=1}^N \bar{LL}_i \quad (13)$$

Then, we apply the usual optimization techniques (quasi-Newton, in particular we use BFGS method or Broyden, Fletcher, Goldfarb and Shanno) to maximize the expression (13). We estimate the parameters' standard errors by information matrix (Hessian inverse).

We obtain the regressor parameters, the standard deviations of random effects and, the inequality persistence or autoregressive. Then, while SYS-GMM method estimates a unique autoregressive parameter, SML method allows us to estimate one for each country. But, as standard deviations include R+, and autoregressive parameters are in the interval [-1, 1], we have to redefine it and maximize on the parameters p:

$$s_i = \sqrt{p_{i,s}^2} \hat{\epsilon} \quad (0, +\infty) \quad r_i = \frac{p_{i,r}}{1 + p_{i,r}} \hat{\epsilon} \quad (-1, +1) \quad (14)$$

As the results of maximization are very sensible to starting values of parameters, then we use values of a previous optimization, i.e. the initial parameters are obtained by the Simulated Annealing procedure taking as initial values those obtained from dynamic panel data.

Finally, if the dependent variable and its first difference are not stationary, the procedures suggested would not be valid, therefore requiring a stationary transformation of the original series. Otherwise the variables could present a cointegration relationship, which requires a different methodology.

A usual transformation is a relative variation to study how regressors' variations explain annual variations observed in the inequality index. Several secondary objectives are achieved: first, both the regressors and the dependent variable are expressed in the same terms (percentage), so that the interpretation of the parameters is more straightforward; and second, it avoids the problem of modeling a censored dependent variable. In this case, the model is:

$$\begin{aligned}
 eq_{i,t} &= a x_{i,t} + b y_{i,t} + g z_{i,t} + e_{i,t} \\
 i &= 1, \dots, N \quad t = 2, \dots, T \\
 eq_{i,t} &= \frac{EQ_{i,t} - EQ_{i,t-1}}{EQ_{i,t-1}} \quad x_{i,t} = \frac{X_{i,t} - X_{i,t-1}}{X_{i,t-1}} \\
 y_{i,t} &= \frac{y_{i,t} - y_{i,t-1}}{y_{i,t-1}} \quad z_{i,t} = \frac{Z_{i,t} - Z_{i,t-1}}{Z_{i,t-1}}
 \end{aligned} \tag{15}$$

This transformation usually solves problems of endogeneity and autoregressive, so the model is estimated as a static panel data by GLS.

### 3. DATA

We use the data compiled by Martorano and Cornia (2011). Their database has annual Gini observations for 18 Latin American countries. The period of analysis is 1990-2008. We transform the variables measured in relative terms (% of GDP) into levels, using the World Bank World Development Indicators. Levels of net disbursements of aid are taken from the OECD-DAC database.

The first step was to select among the potential variables those that theoretically where more closely linked to inequality (see the models in Cornia 2011 for Latin America and Eastern and Central Europe countries and Robinson 2009 for Middle East). A correlation matrix was computed with this preliminary group and those with a significant correlation over  $\pm 10\%$  were rejected due to their multicollinearity problems. Finally, the regressors were grouped as follows (see Appendix A for details and sources):

Domestic redistributive and productive indicators (X): **Pub\_exp** is general government final consumption expenditure; **SOC\_tot** is Social public expenditure; **Tax** is Tax revenue (including social contributions); **Cpi** is the Consumer Price Index; **Agr** and **Ind** are the primary (agriculture) and secondary (industry) sectors in terms of GDP, respectively.

Labour institutions and human capital (Y): **Hc\_low** is the share of adults aged 25-65 with 0 to 8 years of formal education; **Hc\_medium** is the share of adults aged 25-65 with 9-13 years of formal education; **Hc\_high** is the share of adults aged 25-65 with more than 13 years of formal education; **Un** is unemployment; **Mw** is the index of nominal minimum wages deflated by countries.

External redistributive flows (Z): **Tot1** represents international terms of trade; **Fdi** is net foreign direct investment stocks; **Remittance** is workers' remittances receipts;

**Aid** is net ODA received (% of GNI); **Aidpc** is aid per capita; **ODA** is Overseas Development Assistance, as defined by DAC; millions of dollars at 2009 prices.

Dependent variable (EQ): **Gini** is the Gini index on income, calculated on a mixture of net income and gross income concept.

For further analysis, we split the whole sample into two subsamples: one for the lower middle-income Latin American countries (following CEPAL 2010 criteria, these are Bolivia, Ecuador, El Salvador, Guatemala, Honduras, Nicaragua and Paraguay) and the other for the upper middle-income countries<sup>2</sup>.

Table 1 shows sample countries, observations and some descriptive statistics for levels and first differences.

Table 1. Descriptive Statistics

Data in levels									
Countries	observ.	min	mean	max	std.dev	ADF test	KPSS test	Q(1) test	p-value
Argentina	19	44.432	48.358	53.264	2.572	-1.837	0.289	13.958	[0.0002]**
Bolivia	18	49.400	56.359	61.703	3.181	-2.112	0.466	12.060	[0.0005]**
Brazil	19	54.214	58.269	60.379	1.786	-2.507	0.682	13.948	[0.0002]**
Chile	19	51.822	54.289	55.451	1.201	-0.611	0.479	15.336	[0.0001]**
Colombia	19	51.320	55.657	58.900	2.100	-1.856	0.598	12.224	[0.0005]**
Costa Rica	19	43.956	46.711	49.884	1.925	-1.041	0.616	10.459	[0.001]**
Dominican Republic	19	47.208	49.895	51.998	1.363	-1.544	0.347	6.358	[0.0117]*
Ecuador	14	50.157	55.360	58.822	2.399	-0.114	0.523	7.469	[0.0063]**
El Salvador	19	46.102	50.547	53.446	2.128	-0.219	0.469	10.403	[0.0013]**
Guatemala	17	53.227	56.056	58.221	1.420	-0.081	0.509	6.793	[0.0092]**
Honduras	19	52.765	55.249	58.252	1.491	-1.772	0.559	2.456	[0.1171]
Mexico	19	49.760	52.604	54.717	1.680	-0.403	0.541	17.057	[0.0000]**
Nicaragua	14	50.220	53.237	56.331	2.141	-1.419	0.482	12.731	[0.0004]**
Panama	19	52.093	55.235	56.653	1.095	0.545	0.319	6.270	[0.0123]*
Paraguay	14	52.139	55.797	58.377	1.763	-0.125	0.434	5.330	[0.0210]*
Peru	18	46.400	50.604	55.538	3.022	-1.813	0.185	1.695	[0.19297]
Uruguay	19	42.114	43.947	47.056	1.541	-0.098	0.671	14.418	[0.0001]**
Venezuela	19	41.200	44.882	47.633	2.196	-1.979	0.190	8.171	[0.0043]**
Data in first differences									
Countries	observ.	min	mean	max	std.dev	ADF test	KPSS test	Q(1) test	p-value
Argentina	18	-3.332	0.022	2.798	1.457	-2.218	0.299	1.023	[0.3118]
Bolivia	17	-3.234	0.158	4.700	2.234	-4.306	0.120	1.079	[0.2989]
Brazil	18	-1.021	-0.342	0.105	0.337	-2.250	0.513	3.158	[0.0755]
Chile	18	-0.913	-0.177	0.316	0.368	-1.995	0.328	7.676	[0.0056]**
Colombia	18	-1.102	0.388	2.257	0.941	-2.613	0.088	0.030	[0.8619]
Costa Rica	18	-1.223	0.261	4.098	1.322	-3.194	0.070	2.549	[0.1104]
Dominican Republic	18	-3.529	0.061	1.976	1.310	-2.965	0.095	1.177	[0.2780]
Ecuador	13	-3.717	-0.510	0.986	1.317	-2.054	0.263	0.290	[0.5899]

<sup>2</sup> The only difference between CEPAL and other classifications for lower middle-income countries such as World Bank or DAC is Ecuador who is considered upper middle-income country.

El Salvador	18	-3.578	-0.320	1.290	1.359	-3.184	0.148	1.216	[0.2702]
Guatemala	16	-2.576	-0.208	2.011	1.187	-6.306	0.039	0.303	[0.5818]
Honduras	18	-3.654	0.101	2.950	1.717	-4.332	0.076	4.033	[0.0446]*
Mexico	18	-1.411	-0.092	0.971	0.687	-3.226	0.316	1.972	[0.1602]
Nicaragua	13	-1.340	-0.249	1.664	0.924	-0.712	0.187	0.355	[0.5511]
Panama	18	-1.392	-0.162	1.106	0.779	-2.960	0.380	0.000	[0.9977]
Paraguay	13	-2.917	-0.480	0.944	1.095	-2.499	0.130	0.022	[0.8828]
Peru	17	-6.670	0.037	3.763	2.767	-3.091	0.232	0.474	[0.4911]
Uruguay	18	-2.364	0.130	1.305	0.885	-5.784	0.130	3.145	[0.0762]
Venezuela	18	-4.161	-0.072	2.296	1.711	-2.713	0.316	0.155	[0.6936]

Note: (\*) and (\*\*) denote significant at 5% and 1%, respectively. ADF test is stationary test with intercept and without trend; H0: variable is I(0); the significant values to reject H0 are -3.43; -2.86 and -2.57 at 1%, 5% and 10%, respectively. KPSS is stationary test without trend; H0: variable is I(1); the significant values to reject H0 are 0.74, 0.46 and 0.35 at 1%, 5% and 10%, respectively. Q(lag=1) is autoregressive Box Pierce test with H0: No serial correlation; we accept H0 when prob. is high [Q < Chisq(lag)].

Source: Author's elaboration.

The panel is unbalanced mainly because Gini observations were not available for all countries and years. Gini average reaches 52.39 with a maximum of 61.70 (Bolivia in 2000) and a minimum of 41.20 (Venezuela in 2008). Standard deviations show a wide dispersion (1.095-3.181), which means a strong heterogeneity among sample values. Additionally, all time series show order 1 autocorrelation [Box-Pierce test, Q(1)], except Honduras and Peru. In other words, inequality is highly persistent.

Two tests for stationarity were run: the standard Dickey-Fuller Augmented (DFA) and other more consistent for small samples, such as KPSS. This selection is explained because panel data unit roots tests are average variations around DFA (Im et al., 2003) and KPSS (Hadri, 2000). Taking into account both tests, only Argentina, Panama, Peru and Venezuela are not stationary in levels. Considering first differences time series, the autocorrelation only applies for Chile and Honduras, whilst unit roots tests only reject stationarity for Argentina.

#### 4. EMPIRICAL EVIDENCE.

Our first step was to analyse the individual effects (fixed or random) using the Hausman test. Table 2 shows the results for the three samples considered.

Table 2. Hausman test

Samples	Hausman test	p-value
Whole sample	1.6438	[0.9901]
Lower middle income	4.9012	[0.6720]
Upper middle income	5.0260	[0.5405]

Note: H0 is that the estimates of random effects and fixed effects do not differ substantially, if H0 is rejected then select a fixed effects model.

Source: Author's elaboration.

As it can be seen, the Hausman test is not rejected in any of the samples. This implies random effects estimation for all models. Bearing in mind these results, we estimate model [1] as a static panel data with random effects. The consistent estimation procedure is GLS. Results are shown in Table 3.

Table 3. Results of static panel data estimated by GLS within-between

Samples	Whole sample		Upper-middle income		Lower-middle income	
	Coefficient	t-prob	Coefficient	t-prob	Coefficient	t-prob
pub_exp	0.1067	[0.015]*	0.2133	[0.031]*	0.5556	[0.000]**
tot1	-0.0273	0.237				
fdi	0.0651	[0.003]**	0.0782	[0.001]**	0.0378	0.115
remittance	-0.0831	[0.000]**	-0.3565	[0.018]*	-0.1040	0.141
aid	-0.2649	0.224	-0.6651	[0.046]*	-0.3371	[0.002]**
cpi					0.0314	[0.041]*
hc_low	0.6000	[0.018]**	0.5905	[0.000]**		
hc_medium	0.1825	[0.000]**				
hc_high	0.8431	[0.001]**	0.1405	[0.013]*		
un	0.2513	[0.000]**	0.8515	[0.000]**	-0.5895	[0.000]**
R <sup>2</sup>	63.87%		49.53%		59.79%	
AR(1) test N(0,1)	4.737	[0.000]**	5.989	[0.000]**	4.5283	[0.000]**
AR(2) test N(0,1)	0.4873	[0.626]	1.642	[0.101]	1.384	[0.166]

Note: (\*) and (\*\*) denote significant at 5% and 1%, respectively.

Source: Author's elaboration.

Table 3 shows order 1 autocorrelation in residuals. This means that income inequality persistency and endogeneity are detected in Latin American data. The consequences of these facts are that the results are not consistent.

To deal with this limitation we transformed the model into a dynamic panel data and re-estimated it. Table 4 offers the results.

Table 4. Results of dynamic panel data estimated by SYS-GMM

Samples	Whole sample				Upper-middle income				Lower-middle income			
	None transformations		Differences transf.		None transformations		Differences transf.		None transformations		Differences transf.	
	Coef.	t-prob	Coef.	t-prob	Coef.	t-prob	Coef.	t-prob	Coef.	t-prob	Coef.	t-prob
pub_exp	0.7344	[0.003]*	1.2183	[0.000]**	1.6335	[0.000]**	1.6313	[0.000]**	0.9295	[0.000]**	0.8470	[0.024]*
tot1	0.1665	[0.000]*	0.0885	[0.000]**	0.1811	[0.019]*	0.0844	0.0650	0.1063	[0.000]**	0.0703	[0.003]*
fdi	0.0870	[0.216]	0.1428	[0.004]**	0.0560	0.2280	0.0085	0.9190	0.1430	[0.000]**	0.0864	[0.000]**
remittance	0.0900	[0.690]	0.0157	0.9350	0.6147	0.0660	0.4134	0.2710	0.1557	[0.081]	0.0569	0.641
aid	0.3039	[0.115]	0.2784	0.3410	4.0510	0.1560	7.0779	0.0960	0.4634	[0.000]**	0.1827	[0.020]*
hc_low	0.4283	[0.000]*	0.4481	[0.000]**					0.4221	[0.000]**	0.4760	[0.000]**
hc_high					0.4066	0.1900	0.5812	[0.015]*				
un					0.2741	0.2220	0.5936	[0.000]**	0.7547	[0.000]**	0.3525	0.064
Sargan	68.36	[1.000]	43.9	[1.000]	79.5	[1.000]	46.29	[1.000]	44.05	[1.000]	15.9	[1.000]

test			8		1						7	
		[0.008]	-	[0.021]	2.36	[0.018]					-	
AR(1) test	2.642	**	2.30	*	2.36	*	0.2441	[0.807]	1.147	[0.251]	1.85	[0.064]
		[0.013]	-						0.022		0.28	
AR(2) test	2.483	*	1.14		1.88	[0.060]	0.3973	[0.691]	99	[0.982]	03	[0.779]

Note: (\*) and (\*\*) denote significant at 5% and 1%, respectively.

Source: Author's elaboration.

Table 4 shows different results when series in levels or in first differences are used. Considering the previous result that some series in levels are not stationary, we continue the estimation using the transformed series. First of all, Sargan test shows the validity of instruments. The main factors explaining inequality are:

Domestic redistributive policies; only public consumption (**Pub\_exp**) is statistically significant in all samples and its sign is positive. That is, the higher public consumption, the higher inequality is. The effect is more remarkable in upper middle-income countries.

Human capital and labour market institutions: low human capital (**hc\_low**) is positive and statistically significant for the total sample and for lower middle-income countries. High human capital (**hc\_high**) is positive and significant for the upper middle-income countries sample. Unemployment (**Un**) is also positively correlated in upper middle-income countries.

External financial flows: terms of trade (**Tot1**) have a positive and significant effect in all samples (either in levels or first differences). The effect is higher in lower middle-income countries. Foreign direct investment (**Fdi**) in differences is also positive and significant in the total sample and lower middle-income countries. Foreign aid (**Aid**) is negative and significant for lower middle-income countries. In other words, aid has had an egalitarian effect in the seven Latin American lower middle-income countries.

To sum up, public consumption, years of formal education (human capital) and labour market institutions are significant domestic factors to explain income inequality in Latin America. External factors do too: foreign investment increases inequality whereas foreign aid reduces it. Interestingly enough, remittances were not significant. In a further step, we deal with inequality persistence. We estimate an autoregressive panel data model in order to study the influence of this feature. Table 5 shows the results.

Table 5. Results of AR(1) dynamic panel data estimated by SYS-GMM

Samples	Whole sample				Upper-middle income				Lower-middle income			
	None transformations		Differences transf.		None transformations		Differences transf.		None transformations		Differences transf.	
Dynamic model	Coef.	t-prob	Coef.	t-prob	Coef.	t-prob	Coef.	t-prob	Coef.	t-prob	Coef.	t-prob
gini(-1)	0.9095	[0.000]**	0.8080	[0.000]**	0.9771	[0.000]**	0.8989	[0.000]**	0.7111	[0.000]**	0.6843	[0.000]**
pub_exp	0.1027	0.0800	0.3067	[0.000]**	0.1002	0.283	0.2798	[0.037]*	0.4267	[0.000]**	0.4925	[0.001]**
tot1	0.0007	0.9380	0.0007	0.9400	-0.0120	0.3150	0.0096	0.4150	0.0061	0.689	0.0113	0.541
Fdi	0.0100	0.3940	0.0130	0.3370	-0.0058	0.5370	0.0345	0.3250	0.0387	[0.040]*	0.0356	0.165
remittance	-0.0107	0.6380	0.0114	0.8610	-0.0429	0.5430	0.0123	0.9280	-0.1435	[0.000]**	0.1394	[0.012]*

Aid	-0.0696	0.0950	0.1488	[0.040]*	0.5540	0.2930	1.2023	0.0950	-0.1394	[0.002]**	0.1519	0.078
hc_low	0.0557	[0.019]*	0.1034	[0.001]**					0.1435	[0.000]**	0.1495	[0.000]**
hc_high					0.0576	0.4930	0.0980	0.5840				
Un					0.0007	0.9910	0.0827	0.1910	0.1557	[0.000]**	0.1400	[0.030]*
Sargan test	138.1	[0.930]	185.6	[0.119]	108.9	[1.000]	134.1	[0.952]	41.96	[1.000]	83.58	[1.000]
AR(1) test	-1.169	[0.242]	-2.843	[0.004]**	-1.145	[0.252]	-2.189	[0.029]*	-1.694	[0.090]	-1.674	[0.094]
AR(2) test	0.2624	[0.793]	0.6785	[0.497]	-0.8665	[0.386]	0.3905	[0.696]	-0.8597	[0.390]	0.3478	[0.728]

Note: (\*) and (\*\*) denote significant at 5% and 1%, respectively.

Source: Author's elaboration.

As Table 5 shows, inequality persistence is significant in all samples. The higher effect is in the upper middle-income countries. Public consumption remains positive and significant whilst terms of trade are not when lagged inequality is introduced in the model as an instrumental variable. Foreign direct investment and low human capital are still positive and significant in lower middle-income countries, whereas aid is still negative and significant. An interesting novelty is that remittances are now positive and significantly correlated with inequality in the mentioned subsample.

We also deal with the non-linearity of inequality. To our knowledge, this is the first time it is done. We consider a double-censored dynamic panel data. In this model, heterogeneity and autocorrelation parameters are estimated individually. Each sample country has its own estimation. Table 6a shows the parameters associated to regressors, whilst Table 6b shows the parameters for individual effects under random heterogeneity and autocorrelation.

Table 6a. Results of double censored dynamic panel data estimated by SML (parameters)

Samples	Whole sample		Upper-middle income		Lower-middle income	
	Coef.	t-prob	Coef.	t-prob	Coef.	t-prob
pub_exp	0.3175	[0.026]*	0.3733	[0.002]**	0.6372	[0.000]**
tot1	0.0146	[0.027]*	0.0302	[0.006]**	0.0543	[0.062]
fdi	0.0533	[0.031]*	-0.1041	[0.026]*	0.1059	[0.000]**
remittance	-0.0380	[0.457]	-0.0219	[0.481]	-0.0533	[0.151]
aid	-0.0490	[0.041]*	0.0811	[0.131]	-0.2439	[0.023]*
cpi					-0.0992	[0.517]
hc_low	0.5702	[0.000]**			0.6001	[0.000]**
hc_medium	0.4498	[0.394]				
hc_high	0.6756	[0.000]**	0.4372	[0.000]**	-0.8933	[0.000]**
un	0.1063	[0.000]**	0.2817	[0.000]**	0.2536	[0.036]*
pseudo-R <sup>2</sup>	98.85%		98.53%		98.95%	
AR(1) test	1.187 [0.235]		1.473 [0.141]		1.621 [0.105]	
AR(2) test	1.116 [0.264]		1.184 [0.236]		1.551 [0.121]	

Note: (\*) and (\*\*) denote significant at 5% and 1%, respectively. Specifically, 2500 simulations have been performed and have discarded the first 500 to obtain a better convergence of the simulated process.

Source: Author's elaboration.

Table 6b. Results of double censored dynamic panel data estimated by SML  
(persistence: rho, heterogeneity: sigma)

Samples	Whole sample				Upper-middle income				Lower-middle income			
	Rho	t-prob	Sig ma	t-prob	Rho	t-prob	Sigma	t-prob	Rho	t-prob	Sig ma	t-prob
Countries	0.824	[0.011]	1.52	[0.000]	0.78	[0.000]	1.664	[0.000]				
Argentina	5	*	70	**	93	**	2	**				
Bolivia	0.684	[0.041]	1.71	[0.000]					0.71	[0.043]	1.67	[0.000]
	6	*	40	**					65	]	72	**
Brazil	0.974	[0.000]	1.12	[0.004]	0.96	[0.000]	1.203	[0.000]				
	8	**	37	**	36	**	3	**				
Chile	0.981	[0.000]	1.13	[0.002]	0.98	[0.000]	1.568	[0.000]				
	4	**	43	**	33	**	0	**				
Colombia	0.924	[0.000]	1.25	[0.006]	0.94	[0.000]	1.473	[0.000]				
	6	**	43	**	64	**	9	**				
Costa Rica	0.705	[0.008]	1.27	[0.003]	0.72	[0.048]	1.540	[0.000]				
	9	**	79	**	34	*	9	**				
Dominican Republic	0.466	[0.465]	1.42	[0.000]	0.66	[0.548]	1.293	[0.000]				
	5		96	**	13		8	**				
Ecuador	0.944	[0.000]	1.39	[0.000]					0.90	[0.009]	1.42	[0.000]
	9	**	89	**					07	**]	04	**
El Salvador	0.867	[0.024]	1.19	[0.000]	0.79	[0.000]	1.257	[0.000]				
	7	*	75	**	60	**	8	**				
Guatemala	0.640	[0.213]	1.41	[0.000]					0.46	[0.339]	0.91	[0.001]
	8		15	**					36	]	12	**
Honduras	0.259	[0.472]	1.39	[0.000]					0.24	[0.657]	1.03	[0.000]
	0		33	**					71	]	60	**
Mexico	0.944	[0.000]	1.13	[0.000]	0.95	[0.000]	1.157	[0.000]				
	3	**	33	**	88	**	5	**				
Nicaragua	0.862	[0.004]	1.23	[0.002]					0.87	[0.032]	1.23	[0.000]
	3	**	38	**					18	]	60	**
Panama	0.875	[0.061]	1.42	[0.000]	0.72	[0.096]	1.096	[0.000]				
	2		77	**	67		0	**				
Paraguay	0.829	[0.173]	1.16	[0.000]					0.88	[0.221]	1.34	[0.002]
	4		91	**					95	]	76	**
Peru	0.576	[0.328]	1.94	[0.000]	0.53	[0.461]	1.884	[0.000]				
	5		49	**	67		7	**				
Uruguay	0.764	[0.026]	1.15	[0.000]	0.77	[0.000]	1.311	[0.000]				
	2	*	47	**	42	**	8	**				
Venezuela	0.683	[0.045]	1.46	[0.000]	0.66	[0.036]	1.785	[0.000]				
	3	*	45	**	81	*	3	**				

Note: (\*) and (\*\*) denote significant at 5% and 1%, respectively.

Source: Author's elaboration.

As Table 6a shows, taking into account individual random effects and autocorrelation does not change our main results. Public consumption, low human capital, unemployment, terms of trade and foreign direct investment are positively correlated with inequality (although in the upper middle income countries, FDI is negative). Aid is still negative and significant for the total sample and for the lower middle-income countries.

Table 6b shows that inequality persistence is more significant in upper middle-income countries (only Ecuador shows a significant parameter among lower middle-income countries). The Ecuadorian value fits between 0.67 and 0.98, which indicated a high-income inequality autocorrelation. Remarkably enough, random effects are fairly high and different among countries. Argentina, Bolivia, Peru and Venezuela

show high values, whereas Brazil, Mexico and Panama have lower levels of this feature.

Finally, to deal with the non-stationarity assumption, we estimate a static panel data model (15) in first differences by GLS. Table 7 shows the results.

Table 7. Results of relative variations static panel data estimated by GLS within-between

Samples	Whole sample		Upper-middle income		Lower-middle income	
	Coef.	t-prob	Coef.	t-prob	Coef.	t-prob
SOC_tot			0.0107	[0.343]	0.0002	[0.988]
SOC_edu	-0.0137	[0.031] *				
tot1	-0.0343	[0.015] *				
fdi	0.0085	[0.022] *	0.0084	[0.031]*	0.0052	[0.738]
remittance	-0.0003	[0.808]	-0.0009	[0.455]	0.0032	[0.427]
AIDpcc	0.0001	[0.722]	0.0003	[0.921]	-0.0126	[0.042]*
un	0.0214	[0.004] **			0.0273	[0.005]**
hc_medium	-0.1559	[0.001] **	-0.1855	[0.004]*		
hc_high	0.0638	[0.002] **	0.0967	[0.000] **		
agr					-0.0368	[0.071]
ind			-0.0383	[0.011]*		
R <sup>2</sup>	10.93%		12.30%		15.49%	
AR(1) test	-1.767	[0.077]	-0.8197	[0.412]	-1.729	[0.084]
AR(2) test	-1.068	[0.285]	-0.0592	[0.953]	-1.44	[0.150]

Note: (\*) and (\*\*) denote significant at 5% and 1%, respectively.

Source: Author's elaboration.

In this case, human capital (medium and high) and foreign direct investment explain significantly inequality among upper middle-income countries. In lower middle-income countries, unemployment and aid (this time in per capita terms) are significant predictors of inequality.

It is worth enough mentioning that the use of differenced series reduces multicollinearity among regressors. This fact explains that agricultural (for the lower middle-income sample) and industrial (in the case of upper middle-income sample) value added are now significant.

Remarkably enough, none of the public spending variables (except educational and for total sample) were statistically significant.

## 5. CONCLUSION.

Whereas the relationship between aid and growth has been largely investigated, this is not the case for aid and inequality. Latin America is the most unequal region all over the world. These facts justify the interest of this paper.

Literature has organised drivers of inequality around three vectors: domestic redistributive and productive policies; human capital and labour market institutions; and trade and external financial flows.

We use an empirical approach to the study of inequality in 18 Latin American countries for 1990-2008. We deal with endogeneity, autocorrelation and multicollinearity. We use static and dynamic panel data, autoregressive and double-censored models.

Contrary to previous literature, we find that aid has had an egalitarian effect in Latin American countries. In addition, public consumption, human capital, unemployment, terms of trade and foreign direct investment have a positive and significant relationship with income inequality. Remarkably enough, neither taxes nor social public spending and remittances are significantly linked to inequality.

The results are stronger in the case of the lower middle-income subsample.

Finally, persistence –measured as first order autocorrelation- is higher in upper middle- income countries than in lower middle-income countries. Conversely, dispersion does not discriminate incomes. Countries with the highest dispersion are Argentina, Bolivia, Peru and Venezuela, whilst Brazil, Mexico and Panama are the countries with the lowest dispersion.

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## APPENDIX A. LIST OF VARIABLES AND SOURCES

Dependent variable:

**Gini**= Gini index on income, calculated on a mixture of net income and gross income concept (see IDLA Appendix 2 for details).

Domestic redistributive and productive indicators (Xt):

**Pub\_exp**= general government final consumption expenditure (% of GDP) (WDI)

**SOC\_tot**=Social public expenditure as percentage of GDP (CEPALSTAT)

**Tax**= Tax revenue (including social contributions) as % of GDP (CEPALSTAT)

**Agr**= Agriculture Value Added (as a % of GDP) (WDI)

**Ind**= Industry Value Added (as a % of GDP) (WDI)

**Cpi**= inflation measured by the average consumer price. Data for inflation are averages for the year, not end-of-period data. The index is based on annual percent change (WEO)

Labour institutions and human capital (Yt):

**Hc\_low**=share of adults aged 25-65 with 0 to 8 years of formal education (SEDLAC)

**Hc\_medium**=share of adults aged 25-65 with 9-13 years of formal education (SEDLAC)

**Hc\_high**=share of adults aged 25-65 with more than 13 years of formal education (SEDLAC)

**Un**=Unemployment, total (% of total labour force) (WDI)

**Mw**=index of nominal minimum wages deflated by countries' CPI (2000=100). The indicator corresponds to the minimum wages for the formal sector (CEPALSTAT)

External redistributive flows (Zt):

**Tot1**=international terms of trade, fob (2000=100) (CEPALSTAT)

**Fdi**=Net foreign direct investment stocks measured as percentage of GDP (UNCTAD)

**Remittance**= Worker's remittances receipts as percentage of GDP (USAID, UNCTAD, WDI)

**Aid**=net ODA received (% of GNI) (WDI)

**Aidpc**= Aid per capita (WDI)

**ODA**= Overseas development Assistance, as defined by DAC; millions of dollar at 2009 prices (OECD-DAC)