Fighting Corruption: The Corruption-Inequality Trap in Latin America

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Abstract

Using Instrumental Variables estimations and correcting for measurement error, this article shows that corruption has an equalizing effect on income distribution; and, in turn, that inequality tends to increase the level of corruption. For the first time, there is evidence of the existence of a corruption-inequality trap in Latin America. Attempts to reduce corruption directly will increase inequality, consecutively, this will increase corruption, returning in the best of cases to the initial point. The fight against corruption will not be fruitful if, at the same time, inequality in the region is not addressed.

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Introduction

Latin American countries suffer from a common evil: corruption. The region is considered the second with the most corruption. In 2010, according to the Bayesian Corruption Indicator, of 100 possible points (a higher score reflects greater corruption) South Asia obtained 54 points, Africa 56, East Asia 49 and Latin America 55. In this study, corruption is defined as the abuse of authority by public servants to pursue their private interest (Blackburn & Forgues-Puccio, 2009).

At the same time, if Latin America is not the most unequal region, then it is very close to being it. In 2010, according to the Gini index (after taxes and transfers) obtained from version 6.0 of the Standardized World Income Inequality Database, out of 100 available points, on average, Africa has 41 points, East Asia 38, South Asia 39 and Latin America 46. Although there is no quality data for half of the African countries, this figure is still alarming.

The causal effect of corruption on inequality has been commonly studied. The consensus is that corruption is bad for inequality (Gyimah-Brempong & de Munoz, 2006; Gyimah-Brempong, 2002; Jong-Sung & Khagram, 2005; Gupta et al., 2002; Li et al., 2000; Pedauga et al., 2017). Even, Pedauga et al. (2017) finds that corruption increases the Gini index for a sample of Latin American countries. However, there is also evidence that corruption has an equalizing effect in Latin America (Dobson & Ramlogan-Dobson, 2010; Andres & Ramlogan-Dobson, 2011; Dobson & Ramlogan-Dobson, 2012). Moreover, Pedauga et al. (2017) argue that the mistake of Andres & Ramlogan-Dobson (2011) is in not considering the measurement error in the inequality data, which would lead to biased coefficients. In other words, there is contradictory evidence about the effect of corruption on income inequality in Latin America.

The Pedauga et al. and Ramlogan-Dobson et al. debate is clarified and resolve in the favor of the latter. This study brings together recommendations from both studies to obtain a better series of results. To control for measurement error, as Pedauga et al. (2017) recommend, the relationship between corruption and inequality is estimated with the Generalized Latent and Mixed Model (GLLAMM) technique. To control for endogeneity, following Dobson & Ramlogan-Dobson (2012), the Instrumental Variables (IV) approach is used. Corruption is instrumented with an index of the presence of democracy (Dobson & Ramlogan-Dobson, 2012; Gupta et al., 2002) and the rate of settler mortality (Dobson & Ramlogan-Dobson, 2012; Gyimah-Brempong & de Munoz, 2006; Gyimah-Brempong, 2002).

Unfortunately, little attention has been given to the effect of inequality on corruption. Particularly in Latin America there is no study on the subject. This lack of research is surprising given that there are theoretical bases to think that inequality would tend to increase corrupt practices. Greater inequality would push the poor to seek redistributive policies (Meltzer & Richard, 1981) which would encourage the rich to influence public policy through tax evasion, bribes or lobbying (E. Glaeser et al., 2003). Empirically, Jong-Sung & Khagram (2005) finds, with a panel for countries from all the world, that inequality tends to increase the level of corruption. To test this relationship in Latin America, income inequality is instrumented with the proportion of 'mature' population (40 to 59 years) with respect to the total adult population (15 to 69 years). Jong-Sung & Khagram (2005) and Leigh (2006) have already followed this same technique.

This study shows that corruption has an equalizing effect on the distribution of income, however, evidence is also provided that income inequality increases corruption in the region. Therefore, Latin America is in a kind of Corruption-Inequality trap. It can be understood in three steps. First, a decrease in corruption would lead to an increase in income inequality. Second, the increase in inequality would lead to greater corruption. Third, the empirical estimates in the sixth and seventh section show that the second effect is greater than the first, so that the final level of corruption would be, at best, similar to the initial one. The research so far suggested that to combat corruption, governance should be improved through better and more effective institutions. The results of this study suggest that this could harm inequality and even have no effect on corruption. In addition to building stronger institutions, Latin America must fight directly against inequality.

The study is organized as follows.The second section reviews the existing literature. Theoretical arguments are detailed on why corruption can reduce income inequality and why inequality can lead to more corruption. The hypotheses to be evaluated are also given. The third section specifies the empirical strategy to follow.

Three different models are estimated, the first uses GLLAMM, and the second and third IV. The fourth section addresses the data that will be used in the empirical strategy. New measures of corruption and income inequality are used to further control the measurement error. The fifth section presents the results of using the GLLAMM estimation to evaluate the simple relationship between corruption and inequality. The sixth section shows that corruption has an equalizing effect on the distribution of income in Latin America. The seventh section shows the causal effect in the opposite direction, that is, the effect of inequality on corruption. Finally, the article concludes and presents public policy recommendations in the eighth section.

Literature Review

Theoretically, it is not possible to identify the effect of corruption on inequality. On the one hand, according to Andres & Ramlogan-Dobson (2011), corruption can increase inequality, at least, in two ways. First, corruption in the form of tax evasion and exemptions would reduce the funds available to carry out social programs with the aim of reducing poverty. In addition, the beneficiaries of the evasions are usually the rich, so the tax burden would tend to fall on those who lack the means to incur in evasions. In other words, corruption can be seen as a regressive tax. Second, corruption could directly affect the amount of resources allocated to the poor, and even when the amount of money is not reduced, these could be diverted to benefit the rich. For example, spending on education could go from primary to tertiary education.

On the other hand, corruption could lead to greater inequality due to the size of informal markets in the region. Workers in the informal sector tend to be also members of the poorest population (Chong & Calderon, 2000). Informality allows for an income to individuals who can not be inserted in the formal sector due to personal characteristics, institutional barriers or job discrimination (Andres & Ramlogan-Dobson, 2011). According to Chong & Calderon (2000), reforms aimed at reducing corruption would imply additional costs to informal workers as they alter the mechanism through which informal transactions are carried out. Given that the informal sector mainly employs members of the lowest income deciles, institutional improvements that lead to reductions in corruption would lead to a relative and absolute reduction in the income of these people.

Since, theoretically, the effect of corruption on inequality can not be identified, empirical results are key. In studies carried out considering the world as a whole and regions other than Latin America (Gyimah-Brempong & de Munoz, 2006; Gyimah-Brempong, 2002; Li et al., 2000; Gupta et al., 2002; Jong-Sung & Khagram, 2005), corruption has been found to have an increasing effect on the inequality of income distribution. However, different studies have found different relationships between both variables in Latin America. The debate is played, on the one hand, by Pedauga et al. (2017) and, on the other, by Dobson & Ramlogan-Dobson (2010, 2012) and Andres & Ramlogan-Dobson (2011). The first side argues that, as in the rest of the world, corruption increases inequality in the region. The second group argues that the opposite is true and attributes this effect to the presence of long informal markets that offer opportunities to generate income for the economically vulnerable population.

However, the present study found an error in the study of Pedauga et al. (2017). The authors misinterpreted the growth direction of the Control of Corruption Index created by the World Bank. The error is common since the higher the index the less corrupt the country is. Unfortunately, the study published in Applied Economics, journal edited by the CEMA University in Argentina, has influenced the debate and generated false doubts about the rigorous work, published in journals such as World Development and the Journal of Development Studies, Ramlogan-Dobson and its co-authors have written.

The effect of inequality on corruption is theoretically clearer. As inequality increases, the rich have more resources, as compared to the poor, to influence legally or illegally. The rich, as a group of interest, can use lobbying, political contributions or bribes to make the process of creating laws and policies benefit them (E. Glaeser et al., 2003). In turn, as inequality increases, the relatively poorer population will demand a greater distribution of wealth through progressive taxes (Meltzer & Richard, 1981). The pressure for redistribution of wealth would lead the rich to be more motivated to incur in corruption to lower taxes and/or avoid tax collection (Jong-Sung & Khagram, 2005). Therefore, the rich have more motivation and ability to behave corruptly in the face of increases in inequality. Empirically, using a panel with countries from all the World, Jong-Sung & Khagram (2005) find that inequality tends to increase the level of corruption. However, the effect has not been studied formally in Latin America.

The above discussion allows to formulate two hypotheses that will be evaluated empirically in the present study.

Hypothesis 1 (H1): *Corruption decreases income inequality in Latin America.*

Hypothesis 2 (H2): *Income inequality increases corruption in Latin America.*

If both hypotheses were fulfilled, evidence of the following proposition would be available.

Proposition 1 (P1): *A Corruption-Inequality Trap exists in Latin America.*

Past research analyzing the double causality has shown that inequality causes the poor development of institutions, which consecutively leads to greater inequality (Sonin, 2003; Chong & Gradstein, 2007). In turn, Chong & Calderon (2000) show that poor countries with high levels of inequality could find themselves in a trap of Bad Institutions-Inequality. Regardless of the best in their institutions, these countries would remain trapped in high inequality. If it is the case that high inequality leads to more corruption, H2, then a trap of Corruption-Inequality would arise.

Using a sample of countries from around the world, Jong-Sung & Khagram (2005) show that there are virtuous/vicious circles of Corruption-Inequality: there is a mutually reinforcing relationship. Improvements in the fight against corruption would lead to reductions in inequality that in turn would lead to less corruption and thus progressively. However, this relationship would not be fully met for Latin America in the face of the evidence from studies like Dobson & Ramlogan-Dobson (2010, 2012) and Andres & Ramlogan-Dobson (2011). A reduction in corruption would increase inequality, which in turn would lead to higher levels of corruption. This means, without directly addressing levels of inequality, the fight against corruption would be rather useless.

Models Specification

To obtain information on the relationship between corruption and income inequality in Latin America, three different sets of equations are estimated. All models will be estimated using a data panel for 18 Latin American countries[1]. The simple relationship is first tested using the GLLAMM technique (Eqn. 2). This technique is very useful when it comes to measurement errors, however, it does not address the reverse causation problem. The causal effect of corruption on income inequality (Eqn. 3) and vice versa (Eqn. 4) is obtained using IV estimates that can cope with endogeneity. For the sake of robustness, several models are estimated with different measures of inequality and corruption for each equation.

A linear relationship between corruption and inequality is assumed, thus, the base equation would be:

$$I_{i,t} = \beta_0 + \beta_1 C_{i,t} + \beta_2 X_{i,t} + \mu_i \tag{1}$$

where $I_{i,t}$ represents the income inequality of country i at the year t, C a corruption measure, X a vector of covariates and μ_i the deviation of country i's true exposure from the mean exposure for covariate X_i. A higher value of I and C represents greater inequality and corruption, respectively.

However, the main challenge in estimating the causal impact of corruption on income inequality is the endogeneity of corruption. A simple Ordinary Least Squares (OLS) regression of Eqn. 1 would most likely yield biased estimates of β_1. Methods like OLS rely on observed correlations in the data to estimate coefficients. Issues like reverse causality, omitted variables and measurement error could result in spurious correlations in the data. Therefore, simple OLS estimates would mistake these correlations as the causal impact of corruption. This study seeks to solve these three different sources of bias.

When adding relevant control variables, vector X in Eqns. 2 and 3, and vector Y in Eqn. 4, to all the models, the possible bias of omitted variables is controlled. All

[1] The set includes Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Peru, Paraguay, El Salvador, Uruguay and Venezuela.

selected variables have a theoretical explanation of how they relate to the dependent variable and have been used previously in published research. In this way, this study seeks to mitigate the bias of the omitted variables.

Rabe-Hesketh et al. (2003) explain that taking into account the error in the measurement of variables when modeling is crucial for at least two reasons: (a) not taking into account the error can lead to biased estimates of the parameters in the regression; and (b) it facilitates the prediction of the true variable for an individual unit. Corruption and inequality measures are usually accompanied by measurement error. Both the preferred corruption measure (BCI) and the inequality measures come from datasets with the specific objective to address measurement error. Particularly, in the construction of the BCI, an algorithm is used to better distinguish between actual changes in corruption levels and those caused by measurement errors. The algorithm uses the persistence of corruption over time and considers different types of measurement errors present in the original data. Solt (2016) argues that long errors in measuring the Gini in the SWIID database are practically eradicated. To further address the measurement error bias, GLLAMM models are estimated (Rabe-Hesketh et al., 2003). Due to its effectiveness in the treatment of measurement error, this technique has been used previously in articles that investigate the relationship between corruption and income inequality (Pedauga et al., 2017; Ríos & Espejel, 2018). A linear relationship, as in Eqn. 1, is assumed. The structure of the GLLAMM model is:

$$\begin{aligned} I^{'}_{i,t} &= I_{i,t} + \eta_{i,t} \\ \eta_{i,t} &\sim N(0, \sigma^2_{\varepsilon}) \\ I^{'}_{i,t} &= \beta_0 + \beta_1 C_{i,t} + \beta_2 X_{i,t} + \mu_i + \eta_{i,t} \end{aligned} \tag{2}$$

the measure of inequality, $I^{'}$, is only a proxy for true inequality I. The measure for year t and the country of Latin America i, differs from $I_{i,t}$ by a measurement error $\eta_{i,t}$ that is normally distributed.

The GLLAMM technique is useful when dealing with measurement error, however, it does not mitigate the inverse causation bias. The IV technique is used to face this kind of bias:

$$
\begin{aligned}
C_{i,t} &= \alpha_0 + \alpha_1 Ins_{i,t} + \theta_{i,t} \\
I_{i,t} &= \beta_0 + \beta_1 C_{i,t} + \beta_2 X_{i,t} + \zeta_{i,t}
\end{aligned} \tag{3}
$$

Eqn. 3 is estimated using the Two-Stage Least Squares (2SLS). The first stage estimates the linear relationship between corruption, $C_{i,t}$, and a set of instruments, $Ins_{i,t}$, with an error $\theta_{i,t}$. The second stage estimates the causal effect of corruption on inequality, with the same vector of covariates X as in the GLLAMM estimates, and an error ζ. Eqn. 3 will help provide evidence for H1.

The choice of the instrument variable is crucial to obtain consistent results. Past research has used the presence of democracy (Dobson & Ramlogan-Dobson, 2012; Gupta et al., 2002) and the rate of settler mortality (Dobson & Ramlogan-Dobson, 2012; Gyimah-Brempong & de Munoz, 2006; Gyimah-Brempong, 2002) as instruments of corruption. This study follows this approach.

The most popular democracy indices such as those manufactured by Freedom House and Polity IV have a high level of measurement error. Acemoglu et al. (in press) develops a dichotomous democracy index that combines information from various sources such as the datasets in Cheibub et al. (2010), Boix et al. (2013), Freedom House and Polity IV. Originally, the index covers the 18 Latin American countries in this study from 1970 to 2010, but in this study it was updated to cover until 2015. It was not until 2015 that all countries from the dataset were considered as democratic.

The research in Acemoglu et al. (2001) provides one of the variables most used as an instrument, the natural logarithm of the mortality rate faced by European settlers. This measure is suitable for Latin America because data is available for each of the 18 countries. Nicaragua and Panama have the highest mortality rates; the lowest are in Argentina and Chile.

Due to its superiority to control endogeneity, the main results of this study are those obtained in the IV models. Perhaps, the main problem with this method is that it does not take into account the measurement error in the inequality variable. That is why the results are verified with the GLLAMM model. There is no perfect way to estimate the relationship between corruption and inequality, which is why in this study three different sets of equations that place special emphasis on undermining biases from inverse causality, omitted variables and measurement error are estimated.

In the set of controls, X, several variables that have been commonly used when examining the relationship between corruption and inequality are included. Following Pedauga et al. (2017), Dobson & Ramlogan-Dobson (2012) and Jong-Sung & Khagram (2005), the sum of exports and imports in relation to GDP, *Openness*, and the natural logarithm of GDP per capita, *GDP*, are included as controls. Increasing the openness of the economy could benefit labor-intensive export sectors, such as manufacturing, reducing inequality (Cornia, 2010). It is possible that the indicator of corruption is really reflecting the effect of economic development, which is why GDP per capita, *GDP*, is a key control variable. It is expected that the higher the *GDP*, the lower the inequality.

Following Pedauga et al. (2017) and Gupta et al. (2002), the total income from natural resources in relation to GDP, *Natural*, is included. A high dependence on natural resources would lead to greater inequality due to the high concentration of their property and, of course, their income (Tornell & Lane, 1999; Gupta et al., 2002). Government's final consumption expenditure in relation to GDP, *Government*, is also added as control variable. A greater provision of goods and services by the government is often found in countries with welfare states. Greater government consumption is expected to lead toward less inequality. To control for education levels, indicators of primary, *Primary*, and secondary, *Secondary*, education are included. According to Dobson & Ramlogan-Dobson (2012), it is expected that, mainly, secondary education relates to lower inequality.

Following Dobson & Ramlogan-Dobson (2012), a measure of the informal sector size obtained from the work of Friedrich Schneider and co-authors (Hassan & Schneider, 2016) is added. The informal sector provides a livelihood for individuals who could not earn income from jobs that require more education or skills. In general, informal workers belong to the poorest sectors of the population (Chong & Calderon, 2000). Latin America has large informal sectors and would be especially affected by movements that affect them. In addition, the intuition in Dobson & Ramlogan-Dobson (2010) and Andres & Ramlogan-Dobson (2011), and the empirical evidence in Dobson & Ramlogan-Dobson (2012) show that the possible equalizing effect of corruption in income distribution is really due to the informal sector. It is expected that informality relates to lower inequality.

An indicator, *MinWage*, of the size of the minimum wage is added. It is expected that a higher minimum wage will have a negative relationship with income inequality (Cornia, 2013). No other study analyzing the effects of corruption on inequality has controlled for the size of the minimum wage. Finally, an index of the degree of ethnic fractionalization, *EthnicF*, is added. It is expected that the greater *EthnicF* is, the greater income inequality will be (Casey & Owen, 2014). However, most likely, there are non-observed variables that affect both inequality and fractionalization. Therefore, *EthnicF* is only used in the IV estimations and, in order to avoid biased coefficients, is instrumented with the logarithm of the absolute value of the corresponding country's latitude. Casey & Owen (2014) show that latitude is directly correlated with fractionalization but lacks any relation to inequality, making it an ideal instrument.

To evaluate H2, this time, the causal effect that inequality has on corruption is tested. Again, the 2SLS method is used:

$$\begin{aligned} I_{i,t} &= \alpha_0 + \alpha_1 Ins_{i,t} + \theta_{i,t} \\ C_{i,t} &= \beta_0 + \beta_1 I_{i,t} + \beta_2 Y_{i,t} + \zeta_{i,t} \end{aligned} \tag{4}$$

In the first stage, the relation between inequality, $I_{i,t}$, and the instrument, $Ins_{i,t}$, with an error $\theta_{i,t}$ is estimated. The second stage estimates the effect of the instrumented inequality on corruption, $C_{i,t}$, with an error $\zeta_{i,t}$. Y is a vector of covariates different from X.

Inequality is instrumented with the proportion of 'mature' population (40 to 59 years) with respect to the total adult population (15 to 69 years). Jong-Sung & Khagram (2005) and Leigh (2006) have already followed this same technique. According to Higgins & Williamson (2002), the 'fattest' age cohorts tend to have lower rewards. When the cohort in the middle, the mature cohort, is relatively fat then income inequality is moderated. When the fat cohorts are young or old adults then inequality is augmented. In other words, the greater the proportion of 'mature' population, the lower the inequality and vice versa. Jong-Sung & Khagram (2005) show that the mature cohort size is a powerful predictor of inequality, and that it has a very weak correlation, if any, with the error term, in this case, $\zeta_{i,t}$.

The set of controls Y in Eqn. 4 includes variables that directly influence the relationship between corruption and inequality. *Openness* is again included. There are at least two reasons why greater openness leads to lower levels of corruption. First, greater integration alters the cultural norms and the economic and political structures of the country. Second, increased trade would tend to remove government restrictions that usually lead to corrupt behavior (Sandholtz & Koetzle, 2000; Gokcekus & Knörich, 2006). To control for the education of the population, *Primary* and *Secondary* are added. Individuals with higher levels of education tend to be in favor of civil liberties and against abuses by the government (Truex, 2011; E. L. Glaeser & Saks, 2006). With fewer economic controls, there is less room for bribes and extortions, so greater economic freedom would lead to less corruption (Paldam, 2002; Saha et al., 2009). Therefore, an indicator of economic freedom, *EconomicF*, is added.

The variable *Government* is included as a control for the size of the government. There is ambiguity about the effect that this variable must have. On the one hand, Goel & Nelson (1998) and Arvate et al. (2010) find that a larger 'size' of the government leads to higher levels of corruption. On the other, Goel & Budak (2006) and Goel & Nelson (2010) argue that the higher the government's consumption, the lower the level of corruption. *Natural* is included to control for the income dependency on natural resources. As part of the 'resource course', it is expected that the higher the level of income from natural resources, the higher the level of corruption (Sachs & Warner, 1997; Leite & Weidmann, 1999). Democracy tends to decrease corruption in economies that have crossed a level of GDP per capita of approximately US$2,000 (in 2005 US$) (Jetter et al., 2015). Since in Latin America only Nicaragua, Honduras, Bolivia, and Paraguay are below this threshold, *Democracy* is confidently added to the estimations. In theory, with greater transparency and accountability, there is a greater likelihood of identifying and punishing corrupt behaviors, so less corruption would be expected (Lindstedt & Naurin, 2010). Accordingly, the variable *Transparency* is added to control for this effect.

Variables used as instruments in Eqn. 3 and Eqn. 4 should meet the relevance and exclusion conditions for the estimations to be valid. The relevance condition states that the instruments should be (strongly) related with the endogenous explanatory variable. The exclusion conditions declare that the instruments should not be related to the dependent variable other than through the endogenous variable.

Unfortunately, the exclusion restriction can not be proven in the data. However, several authors in previous published research argue that the selected instruments comply with the exclusion restriction (see Dobson & Ramlogan-Dobson (2012), Gyimah-Brempong & de Munoz (2006), Gyimah-Brempong (2002) and Gupta et al. (2002) for Eqn. 3, and Jong-Sung & Khagram (2005) and Leigh (2006) for Eqn. 4).

The relevance condition is tested using the results in the first stage of the 2SLS. When there is only one endogenous variable, the First stage R-square and the First stage prob $>$ F tests are used to examined the relevance of the instruments (see columns (1), (3), (5) and (6) of Table 4, and all columns in Table 6). In the presence of two endogenous variables, the relevance is tested using Shea's partial R-square (see columns (2) and (4) of Table 4) . All the IV models passed the relevance test (see Tables 4 and 6).

If the endogenous explanatory variable actually is exogenous, then it would be worthwhile to exchange the IV estimator for an OLS estimator because it would be more efficient. The Wooldridge (1995) robust score test and a robust regression-based test are used to check if an IV estimator is needed. The IV technique is worth using only if both tests are significant. In all models estimated, the test statistics were highly significant, hence, our main explanatory variables (corruption in Eqn. 3 and inequality in Eqn. 4) must be treated as endogenous (see Tables 4 and 6).

Data

The results of this work are largely due to new sources of data that have been developed in recent years.

The indicators of corruption most used in the literature are the World Bank's Control of Corruption Index (CCI), the Corruption Perception Index (CPI) of Transparency International and the International Country Risk Guide of Political Risk Services (ICRG). However, many criticisms have been made to these indicators. The most worrisome for our purpose is the inability of these measures to be used in longitudinal analyzes, either panels or time series (Treisman, 2007). First, Transparency International has changed the methodology of the CPI several times over the years so that changes in corruption could be confused with changes due to the new methodology. Second, both Transparency International and the World Bank have varied the sources of their surveys in successive years so that different sources would cause the same thing to happen as with the first point. Furthermore, both Transparency International and the World Bank warn that caution should be exercised in interpreting changes in successive years unless they are large. Finally, there is little transparency in the elaboration of the ICRG. It is not explained how a rating of three means the same as a rating of three from another country. Nor does it explain what appear to be several recalibrations that have caused unexplained leaps in a matter of months.

Researchers have continued to use the CCI, the CPI and the ICRG arguing for the lack of alternatives (Svensson, 2005). They were right. Fortunately, Standaert (2015) develops the Bayesian Corruption Indicator (BCI) with a new methodology that aims to correct the problems of these indexes, including the aforementioned ones. Using a state-space model Standaert expands the methodology used in the World Governance Indicators so that the persistence of corruption allows to identify the real changes in corruption levels. He then estimates the model using a Bayesian Gibbs sampling algorithm that, together with the correction for missing data, allows the model to be estimated without manipulations or additional assumptions. All this allows having an indicator without selection biases, such as the CPI, and which allows comparisons over time. The BCI is available for all the studied countries from 1984 to 2014. As a robustness check, the CCI, available for all the studied countries from 1996 to 2015, is also used as a corruption measure.

Figure 1 shows the ranking for our sampled countries according to their level of perceived corruption. The larger the BCI, the higher the level of perceived corruption. Venezuela, Paraguay and Argentina show the highest levels of corruption between 2005 and 2015; Chile, Uruguay and Costa Rica, commonly referred to as the most prosperous countries in the region, show the lowest levels. Brazil and Mexico, the largest economies in Latin America, are in the least corrupt half of the ranking.

[Figure 1 about here.]

Regarding the measures of inequality, this study uses the 6.0 version of the Standardized World Income Inequality Database (SWIID) developed in Solt (2016). The SWIID is a database of Gini indexes calculated with multiple imputation. It uses primary sources, such as the Socioeconomic Database for Latin America and the Caribbean (SEDLAC) and the Luxembourg Income Study Database (LIS), and also secondary sources, such as the All The Ginis Dataset of the World Bank. The imputation of missing data data allows the SWIID to have the greatest coverage of Gini indexes of both time and space (Ferreira et al., 2015).

As with corruption measures, the problem of comparability between years and countries is a problem that needs to be addressed. Fortunately, the SWIID maximizes comparability and is more suitable for the use of longitudinal panel analysis than any other measure (Solt, 2016). Pedauga et al. (2017) has already used this measure in the analysis of the effects of corruption on inequality in Latin America. As a way to assure robustness in the results, two different Gini indices are obtained from the SWIID. *Net Gini* represents inequality in disposable income (post-taxes and post-transfers), and *Market Gini* the inequality in market income (pre-tax and pre-transfers). The data for both indices is available, at least, from 1990 to 2013 for all the countries studied.

Figure 2 orders the countries in the sample according to their levels of inequality between 2005 and 2015. The higher the Net Gini index, the higher the level of inequality. Interestingly, the country with the highest level of corruption, Venezuela, is the one with the highest income equality. Different sources point to the truth of this data (Oxfam, 2010; CEPAL, 2018). In the last decade and a half, Venezuela has devoted long efforts to poverty reduction or redistributive policies. On the other hand, one of the least corrupt countries, Chile, is also one of the most unequal. Once again, the largest economies in the region, Brazil and Mexico, are in the middle of the table.

[Figure 2 about here.]

To measure the size of the informal sector, *informal*, data from 1999 to 2013 created in Hassan & Schneider (2016) is used. Dobson & Ramlogan-Dobson (2012), in the analysis of the effect of corruption on inequality in Latin America, make use of the same version of data but with less time coverage. Pedauga et al. (2017) use data from the Socio-Economic Database for Latin America and the Caribbean (SEDLAC), however, this source has a significantly lower number of observations. For example, for countries like Nicaragua there are only four years of observations.

From the World Development Indicators of the World Bank the following data is obtained. *Openness*: the sum of exports and imports in relation to GDP. *GDP*: the natural logarithm of GDP per capita. *Natural*: the ratio of income from natural resources to GDP. *government consumption*: government consumption as a percentage of GDP. For education, data in Barro & Lee (2013) is used. *Primary* and *Secondary* represent the population rates over 15 years with primary and secondary education. Data from, at least, 1970 to 2015 is available for all the studied countries.

From the Database of Political Institutions (Cruz et al., 2016), a variable, *Orientation*, that indicates the political orientation of the party in power is used. *Orientation* can take three values: 1 right, 2 center and 3 left. From the database built in Alesina et al. (2003), the variable *EthnicF* is obtained. *EthnicF* reflects the probability that two people randomly selected from the same country do not belong to the same ethnicity or speak a different language. Data for most of the studied countries is available from 1975 to 2012. However, data exists for all the 18 countries.

To measure economic freedom, *EconomicF*, the Index of Economic Freedom 2017 developed by the Heritage Foundation (Miller et al., 2017) is used. The index is a composite of ten 'specific' and quantifiable freedoms. These include business freedom, freedom of exchange, investment freedom and financial freedom. Data from 1995 to 2015 for each of the countries studied is available.

To represent the level of transparency in a determined country, *Transparency*, the Transparency Index developed in Williams (2015) is used. The index covers from 1980 to 2010 for the countries studied. The indicator takes into account that the fact that the government provides more economic, social and financial information does not necessarily translate into accountability on the part of the authorities. Accountability is associated, rather, with information as a mechanism of restriction (Williams, 2015).

Table 1 shows the summary statistics for each of the variables used.

[Table 1 about here.]

The simple relationship between corruption and inequality

Table 2 shows the results of estimating Eqn. 2. The table does not aim to capture the causal effect of corruption of corruption on income inequality, it rather shows the relationship between both variables. To provide robustness to the results, Table 2 uses two different measures of income inequality and corruption. Columns (1) and (2) use the Net Gini index as dependent variable, and columns (3) and (4) use the the Market Gini. Columns (1) and (3) use the BCI as corruption measure, and columns (2) and (4) use the CCI.

[Table 2 about here.]

All four columns show a a negative and statistically significant relationship between corruption and income inequality. Column (1) show that a one unit increase in the BCI is associated with a 0.04 units decrease in the Net Gini index. In column (3), one unit increase in the BCI relates to a 0.142 units decrease in the Market Gini index. More pronounced results are yielded using the CCI as corruption measure (see columns (2) and (4)). The results are robust to different inequality and corruption measures.

In respect to the control variables, higher income inequality is related to lower openness to trade, GDP per capita, minimum wages and smaller informal markets;

and to higher government consumption and dependency on natural resources. Levels of primary and secondary education do not seem to have a clear relationship with income inequality. It was expected that higher public goods and services provision by the government would relate to lower income inequality, however, the positive coefficient of *Government* indicate the opposite.

The results are consistent with Dobson & Ramlogan-Dobson (2010, 2012) and Andres & Ramlogan-Dobson (2011): lower corruption is associated to higher income inequality in the region. Even when controlling for GDP per capita, *GDP*, the relationship remains highly significant to different corruption and inequality measures. These results must be taken with much caution, although the GLLAMM models specified here control for the Gini measurement error, endogeneity in the relationship is still present. For this reason, the GLLAMM estimations are considered in this study as the 'weakest' ones. In the following section, the issue of endogeneity is addressed to show that corruption indeed decreases income inequality.

The effect of corruption on inequality

The above results show a statistically significant relationship between corruption and inequality. However, this relationship could be due to the existence of 'reverse causality'. To test H1, Table 3 shows the results of estimating the same models as Table 2 using the IV technique. In addition, and as a robustness check, the level of ethnic fractionalization, *EthnicF*, is added as a control variable. To further provide robustness, two different measures of income inequality and corruption are used. Columns (1) to (4) use the Net Gini index as dependent variable, and columns (5) and (6) use the the Market Gini. Columns (1), (2) and (5) use the BCI as corruption measure, and columns (3), (4) and (6) use the CCI. In columns (1), (3), (5) and (6), corruption is instrumented with the created democracy index (Acemoglu et al., in press) and the logarithm of the settler mortality rate constructed in Acemoglu et al. (2001); columns (2) and (4) instrument corruption and ethnic fractionalization using the logarithm of the absolute value of the latitude of the respective country in addition to the democracy index and the settler mortality rate. Table 4 show the specification tests results. The *First stage R-sq* and *First stage Prob* $>$ *F* argue in favor of the relevance of the instruments used. The *Wooldridge robust score* and the *Robust regression-based test* show that the relationship between corruption and income inequality should indeed be treated as endogenous. All the models passed all the tests.

[Table 3 about here.]

[Table 4 about here.]

The six columns show a statistically significant causal negative effect of corruption on income inequality. The results are consistent with those of GLLAMM estimations. A decrease in corruption would yield higher income inequality. The outcome is robust to different corruption and inequality measures and to the adding of *EthnicF* as a control variable. A one unit decrease in the BCI causes an increase of 0.31 to 0.37 units in the Net Gini index. The effect is seven to nine times higher that the one found in Table 2, that is when endogeneity is not addressed, the effect of corruption on income inequality is underestimated.

Higher income inequality is related to higher ethnic fractionalization, government consumption, and to smaller informal markets. Note that once endogeneity is addressed, the significant coefficient of *MinWage* disappears, that is, the minimum wage level does not seem to have a relationship with income inequality. Primary education seems to have a negative relationship with income inequality in two columns, while, curiously, secondary education seems to be related to greater inequality in three columns. In contrast to Table 2, a greater reliance on natural resource income is associated with lower income inequality once endogeneity is addressed. Interestingly, a higher Net Gini index is related to higher trade openness, but a higher Market Gini index is related to lower openness. The findings of the control variables are worth research by themselves, however, this study focuses on the relationship between corruption and income inequality, therefore, the explanation of these interesting results is beyond its scope.

As with Table 2, the results coincide with those in Dobson & Ramlogan-Dobson (2010, 2012) and Andres & Ramlogan-Dobson (2011): lower corruption results in higher income inequality. The result provides empirical evidence to H1. In turn, the results differ from those of studies that argue that corruption increases income inequality but that do not study the Latin American region on its own (Gupta et al., 2002; Gyimah-Brempong, 2002; Gyimah-Brempong & de Munoz, 2006; Li et al., 2000). However, the next section will show that Latin America is not different from the rest of the world in relation to the effect of inequality in corruption (Jong-Sung & Khagram, 2005), thus creating a trap between corruption and inequality.

The other way: The effect of inequality on corruption

The GLLAMM model showed a significant correlation between corruption and inequality. Then, with the IV estimations, evidence of the equalizing causal influence of corruption was shown. Instrumenting corruption with democracy and settler mortality, it is shown that corruption decreases inequality in the distribution of income in Latin America. Now, testing H2, Eqn. 4 is estimated to look for the opposite relationship: the effect of inequality on corruption.

Table 5 shows the causal effect of income inequality on corruption. Following Jong-Sung & Khagram (2005) and Leigh (2006), the Net and Market Gini indices are instrumented with the proportion of 'mature' population in the particular country. As with last sections, robustness is provided by using two different measures of income inequality and corruption. Columns (1) and (2) use the BCI as dependent variable, and columns (3) and (4) use the the CCI. Columns (1) and (3) use the Net Gini as inequality measure, and columns (2) and (4) use the Market Gini. Table 6 show the specification tests results. The *First stage R-sq* and *First stage Prob* $> F$ argue in favor of the relevance of the instruments used. The *Wooldridge robust score* and the *Robust regression-based test* show that the relationship between corruption and income inequality should indeed be treated as endogenous. All the models passed all the tests.

[Table 5 about here.]

[Table 6 about here.]

In all the columns, inequality in the distribution of income shows a positive and highly significant coefficient. An increase in the Gini index would lead to an increase in corruption. The result is consistent with the findings of the seminal paper on the topic Jong-Sung & Khagram (2005). Specifically, according to column (1), a one unit increase in Net Gini index is related to an increase of almost one unit in the BCI. The effect is enormous, it is almost a one-to-one ratio, and it is even bigger when the measure of inequality is the Gini Market.

In addition, greater corruption is related to lower levels of dependence on natural resources, economic freedom and transparency, and a higher proportion of the population with secondary education. The results with respect to the dependence on income from natural resources and secondary education still present interesting results that deserve study. Unfortunately, this goes beyond the scope of this paper. Interestingly, the coefficient of *Democracy* is not statistically significant. Globally, democracy is important to determine the level of corruption; Democratic countries are associated with less perceived corruption (Drury et al., 2006). However, this is not true in the case of Latin America: Democracy is not a key to mitigate corruption.

Table 5 provides empirical evidence for H2: higher income inequality produces more corruption. Since lower corruption yields higher income inequality (H1), then there is evidence of P1: there exists a Corruption-Inequality 'Trap' in Latin America. For the first time there is evidence of this kind of trap. A dynamic relationship between these two variables exists: if a country manages to reduce its level of corruption, reflected by a perceived corruption index, it will cause greater inequality, reflected in the Gini index, which in turn will lead to greater corruption. Judging by the size of the coefficients, it is clear that the second effect is greater: any attempt to face corruption, without implementing policies with the aim of reducing inequality, would be counteracted and overcome by the influence of inequality on corruption.

Conclusions with Policy Implications

The present study provides, for the first time, evidence of the existence of a Corruption-Inequality Trap in Latin America. On the one hand, corruption has an equalizing effect on the distribution of income (see Table 3). Unlike the rest of the world

(Gupta et al., 2002; Li et al., 2000; Gyimah-Brempong & de Munoz, 2006; Gyimah-Brempong, 2002), an increase on perceived corruption (BCI) of one point (out of a total of 100) leads to a decrease in the Gini index of between 0.31 and 0.37 points (out of a total of 100). On the other hand, the results in Table 5 suggest that inequality leads to greater corruption, as in the rest of the world (Jong-Sung & Khagram, 2005): a 1 point increase in the Gini index leads to an increase of between 0.95 and 1.45 points in the BCI. The two effects are in opposite directions. Furthermore, the second effect is more than three times greater than the first.

For a panel of 102 countries from all continents, Jong-Sung & Khagram (2005) show evidence of a virtuous/vicious cycle: a fall in corruption leads to an improvement in inequality which in turn leads to a decrease in corruption. To start the cycle you need a push in either corruption or inequality. The cycle does not work for Latin America where it seems that the situation is more serious.

Latin America is in a Corruption-Inequality Trap. Exogenous decreases in corruption, for example, through an independent commission charged with policing politicians, can not only aggravate inequality but lead to a further increase in the level of corruption. Future research will have to identify the exact channels, but for now we know that informality is key (Dobson & Ramlogan-Dobson, 2010, 2012; Ríos & Espejel, 2018). All this means that new attempts to reduce corruption such as the '*java lato*' in Brazil or the new national anti-corruption system in Mexico can be at best useless and at worst damaging to inequality and corruption itself.

Fighting corruption directly can have undesirable consequences. Dobson & Ramlogan-Dobson (2012) propose to take care of aspects related to the informal sector: fight corruption with one hand and with the other build better institutions to improve aspects of governance that allow a better integration into the formal market. The present study shows that this is necessary but not sufficient to fight corruption. It takes three hands. The first seeks to fight corruption directly, it could be through a brand new anti-corruption system as in Mexico; the second is charged with building institutions that support the integration to the formal sector; finally, the third seeks to reduce economic inequality.

Latin American countries can not fight corruption if at the same time they do not seek to reduce inequality more aggressively. Among the results obtained, it is confirmed that the historical legacy of Latin America means bad news for inequality. Evidence is shown that countries with high ethnolinguistic fractionalization such as Bolivia, Brazil, Mexico and Peru will face serious challenges when trying to reduce their inequality. Hard work is required to reduce social exclusion. The following public policies are proposed to meet both objectives; reduce inequality and corruption.

1. Greater and better quality basic education. Table 3 shows that primary education is related to lower income inequality. López-Calva & Lustig (2010) argue that the increase in basic education has led to a reduction in the earnings gap between skilled and low-skilled workers. This, in turn, has been one of the two main causes in the reduction of inequality in Latin America in the past decade.

2. Increase in intensity and quality of large-scale conditional transfer programs, for example, *Jefes y Jefas de Hogar* in Argentina, *Bolsa Familia* in Brazil and *Progresa / Oportunidades / Prospera* in Mexico. According to López-Calva & Lustig (2010), these programs are the second main cause of the reduction in inequality in Latin America.

3. Transparency in information provided by governments that is capable of carrying out accountability. The information must be complemented with ways in which those responsible can be held accountable. Table 5 shows that quality and transparency of information is related to lower corruption.

4. Focus on attacking issues of 'great' corruption, such as tax evasion by larger companies (commonly multinationals) and bribes in government contracting. Ríos & Espejel (2018) show that policies that attack corruption should begin by focusing on sectors that do not upset the balance in informal markets, since they are composed, for the most part, of vulnerable population. Focusing on small corruption like that visible directly on the streets can have serious consequences on the informal sector. The first two proposals in this list will support the reduction of the informal sector naturally.

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The data that support the findings of this study are available from the authors upon reasonable request.

References

Acemoglu, D., Johnson, S., & Robinson, J. A. (2001). The colonial origins of comparative development: An empirical investigation. *American Economic Review*, *91*(5), 1369–1401.

Acemoglu, D., Naidu, S., Restrepo, P., & Robinson, J. A. (in press). Democracy does cause growth. *Journal of Political Economy*.

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., & Wacziarg, R. (2003). Fractionalization. *Journal of Economic Growth*, *8*(2), 155–194.

Andres, A. R., & Ramlogan-Dobson, C. (2011). Is corruption really bad for inequality? Evidence from Latin America. *The Journal of Development Studies*, *47*(7), 959–976.

Arvate, P. R., Curi, A. Z., Rocha, F., & Miessi Sanches, F. A. (2010). Corruption and the size of government: causality tests for oecd and latin american countries. *Applied Economics Letters*, *17*(10), 1013–1017.

Barro, R. J., & Lee, J. W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics*, *104*, 184–198.

Blackburn, K., & Forgues-Puccio, G. F. (2009). Why is corruption less harmful in some countries than in others? *Journal of Economic Behavior & Organization*, *72*(3), 797–810.

Boix, C., Miller, M., & Rosato, S. (2013). A complete data set of political regimes, 1800–2007. *Comparative Political Studies*, *46*(12), 1523–1554.

Casey, G. P., & Owen, A. L. (2014). Inequality and fractionalization. *World Development*, *56*, 32–50.

CEPAL. (2018). La ineficiencia de la desigualdad. *Trgesimo sptimo periodo de sesiones de la CEPAL.*

Cheibub, J. A., Gandhi, J., & Vreeland, J. R. (2010). Democracy and dictatorship revisited. *Public Choice*, *143*(1-2), 67–101.

Chong, A., & Calderon, C. (2000). Institutional quality and income distribution. *Economic Development and Cultural Change*, *48*(4), 761–786.

Chong, A., & Gradstein, M. (2007). Inequality and institutions. *The Review of Economics and Statistics*, *89*(3), 454–465.

Cornia, G. A. (2010). Income distribution under Latin Americas new left regimes. *Journal of Human Development and Capabilities*, *11*(1), 85–114.

Cornia, G. A. (2013). *Inequality trends and their determinants: Latin America over the period 1990–2010*. Oxford University Press.

Cruz, C., Keefer, P., & Scartascini, C. (2016). The database of political institutions 2015 (dpi2015).

Dobson, S., & Ramlogan-Dobson, C. (2010). Is there a trade-off between income inequality and corruption? Evidence from Latin America. *Economics letters*, *107*(2), 102–104.

Dobson, S., & Ramlogan-Dobson, C. (2012). Why is corruption less harmful to income inequality in Latin America? *World Development*, *40*(8), 1534–1545.

Drury, A. C., Krieckhaus, J., & Lusztig, M. (2006). Corruption, democracy, and economic growth. *International Political Science Review*, *27*(2), 121–136.

Ferreira, F. H., Lustig, N., & Teles, D. (2015). Appraising cross-national income inequality databases: An introduction. *The Journal of Economic Inequality*, *13*(4), 497–526.

Glaeser, E., Scheinkman, J., & Shleifer, A. (2003). The injustice of inequality. *Journal of Monetary Economics*, *50*(1), 199–222.

Glaeser, E. L., & Saks, R. E. (2006). Corruption in america. *Journal of Public Economics*, *90*(6-7), 1053–1072.

Goel, R. K., & Budak, J. (2006). Corruption in transition economies: effects of government size, country size and economic reforms. *Journal of Economics and Finance*, *30*(2), 240–250.

Goel, R. K., & Nelson, M. A. (1998). Corruption and government size: A disaggregated analysis. *Public Choice*, *97*(1-2), 107–120.

Goel, R. K., & Nelson, M. A. (2010). Causes of corruption: History, geography and government. *Journal of Policy Modeling*, *32*(4), 433–447.

Gokcekus, O., & Knörich, J. (2006). Does quality of openness affect corruption? *Economics Letters*, *91*(2), 190–196.

Gupta, S., Davoodi, H., & Alonso-Terme, R. (2002). Does corruption affect income inequality and poverty? *Economics of Governance*, *3*(1), 23–45.

Gyimah-Brempong, K. (2002). Corruption, economic growth, and income inequality in Africa. *Economics of Governance*, *3*(3), 183–209.

Gyimah-Brempong, K., & de Munoz, S. (2006). Corruption, growth, and income distribution: Are there regional differences? *Economics of Governance*, *7*(3), 245–269.

Hassan, M., & Schneider, F. (2016). Size and development of the shadow economies of 157 worldwide countries: Updated and new measures from 1999 to 2013. *Journal of Global Economics*, *4*(218), 2.

Higgins, M., & Williamson, J. G. (2002). Explaining inequality the world round. *Japanese Journal of Southeast Asian Studies*, *40*(3), 268–302.

Jetter, M., Agudelo, A. M., & Hassan, A. R. (2015). The effect of democracy on corruption: Income is key. *World Development*, *74*, 286–304.

Jong-Sung, Y., & Khagram, S. (2005). A comparative study of inequality and corruption. *American sociological review*, *70*(1), 136–157.

Leigh, A. (2006). Does equality lead to fraternity? *Economics letters*, *93*(1), 121–125.

Leite, M. C., & Weidmann, J. (1999). *Does mother nature corrupt: Natural resources, corruption, and economic growth*. International Monetary Fund.

Li, H., Xu, L. C., & Zou, H.-f. (2000). Corruption, income distribution, and growth. *Economics & Politics*, *12*(2), 155–182.

Lindstedt, C., & Naurin, D. (2010). Transparency is not enough: Making transparency effective in reducing corruption. *International political science review*, *31*(3), 301–322.

López-Calva, L. F., & Lustig, N. C. (2010). *Declining inequality in latin america: A decade of progress?* Brookings Institution Press.

Meltzer, A. H., & Richard, S. F. (1981). A rational theory of the size of government. *Journal of Political Economy*, *89*(5), 914–927.

Miller, T., Kim, A. B., & Holmes, K. (2017). Index of Economic Freedom. *Washington DC: The Heritage Foundation*.

Oxfam. (2010). *Venezuela: Latin americas inequality success story.* Retrieved 2018-11-5, from https://oxfamblogs.org/fp2p/venezuela-latin-americas-inequality-success-story/

Paldam, M. (2002). The cross-country pattern of corruption: economics, culture and the seesaw dynamics. *European Journal of Political Economy*, *18*(2), 215–240.

Pedauga, L. E., Pedauga, L. D., & Delgado-Márquez, B. L. (2017). Relationships between corruption, political orientation, and income inequality: Evidence from Latin America. *Applied Economics*, *49*(17), 1689–1705.

Rabe-Hesketh, S., Pickles, A., & Skrondal, A. (2003). Correcting for covariate measurement error in logistic regression using nonparametric maximum likelihood estimation. *Statistical Modelling*, *3*(3), 215–232.

Ríos, V., & Espejel, O. (2018). *Who pays the bribe matter: Corruption and income inequality.* (Working paper)

Sachs, J. D., & Warner, A. M. (1997). Sources of slow growth in african economies. *Journal of African economies*, *6*(3), 335–376.

Saha, S., Gounder, R., & Su, J.-J. (2009). The interaction effect of economic freedom and democracy on corruption: A panel cross-country analysis. *Economics Letters*, *105*(2), 173–176.

Sandholtz, W., & Koetzle, W. (2000). Accounting for corruption: Economic structure, democracy, and trade. *International studies quarterly*, *44*(1), 31–50.

Solt, F. (2016). The Standardized World Income Inequality Database. *Social Science Quarterly*, *97*(5), 1267–1281.

Sonin, K. (2003). Why the rich may favor poor protection of property rights. *Journal of comparative economics*, *31*(4), 715–731.

Standaert, S. (2015). Divining the level of corruption: A Bayesian state-space approach. *Journal of Comparative Economics*, *43*(3), 782–803.

Svensson, J. (2005). Eight questions about corruption. *The Journal of Economic Perspectives*, *19*(3), 19–42.

Tornell, A., & Lane, P. R. (1999). The voracity effect. *American Economic Review*, 22–46.

Treisman, D. (2007). What have we learned about the causes of corruption from ten years of cross-national empirical research? *Annual Review of Political Science*, *10*, 211–244.

Truex, R. (2011). Corruption, attitudes, and education: Survey evidence from nepal. *World Development*, *39*(7), 1133–1142.

Williams, A. (2015). A global index of information transparency and accountability. *Journal of Comparative Economics*, *43*(3), 804–824.

Wooldridge, J. M. (1995). Score diagnostics for linear models estimated by two stage least squares. *Advances in econometrics and quantitative economics: Essays in honor of Professor CR Rao*, 66–87.

List of Tables

Table 1: Summary Statistics

VARIABLES	N (1)	mean (2)	sd (3)	min (4)	max (5)
Net Gini	555	47.02	4.589	32.73	57.68
Market Gini	555	49.95	4.687	35.39	61.31
BCI	558	52.28	8.390	30.36	68.31
CCI	306	0.308	0.686	-1.573	1.444
Openness	805	56.15	29.32	10.34	165.3
Primary	612	21.57	8.743	4.780	42.05
Secondary	612	17.44	8.563	2.790	48.07
Informal	255	43.98	16.00	17.75	81.45
Natural	826	4.140	4.595	0.0583	27.68
Government	798	12.20	4.118	2.976	43.48
MinWage	630	123.8	58.11	28.30	479.4
GDP	826	7.607	0.919	5.402	9.734
EthnicF	828	0.427	0.186	0.169	0.740
Transparency	558	57.32	9.021	28	75
Orientation	549	1.842	0.927	1	3
EconomicF	378	61.93	7.978	34.30	79

Notes: This table shows the summary statistics of the variables used in Eqns. 2, 3 and 4. Column (1) shows the number of observations; column (2) the mean; column (3) the standard deviation; column (4) the minimum value; and column (4) the maximum value.

Table 2: Relationship between corruption and income inequality

	Net Gini		Market Gini	
VARIABLES	(1)	(2)	(3)	(4)
BCI	-0.040**		-0.142***	
	(0.020)		(0.015)	
CCI		-0.504***		-1.930***
		(0.122)		(0.160)
Primary	-0.030	-0.071***	0.071***	-0.032*
	(0.027)	(0.017)	(0.024)	(0.018)
Seconday	-0.007	-0.032	-0.035	-0.023
	(0.048)	(0.050)	(0.055)	(0.048)
Openness	-0.039***	-0.012*	-0.046***	-0.060***
	(0.008)	(0.007)	(0.007)	(0.007)
Government	0.396***	0.567***	0.461***	0.366***
	(0.055)	(0.034)	(0.037)	(0.033)
Natural	0.065*	0.069**	0.029	0.086***
	(0.036)	(0.028)	(0.024)	(0.024)
GDP	-3.660***	-3.808***	-3.920***	-4.043***
	(0.486)	(0.474)	(0.527)	(0.450)
MinWage	-0.014***	-0.017***	-0.003	-0.007*
	(0.005)	(0.005)	(0.004)	(0.004)
Informal	-0.009	-0.044***	-0.006	-0.028***
	(0.012)	(0.009)	(0.014)	(0.011)
Constant	79.700***	78.578***	86.376***	86.026***
	(4.685)	(3.800)	(5.208)	(3.646)
Observations	249	215	249	215

Notes: This table shows four different models to estimate the relationship between corruption and income inequality. All models were estimated using the GLLAMM technique. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.
Columns (1) and (3) use the BCI as corruption measure; columns (2) and (4) use the more traditional CCI. Columns (1) and (2) use the Net Gini index as dependent variable; columns (3) and (4) use the Market Gini Index.

Table 3: Corruption effect on income inequality

	Net Gini				Market Gini	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
BCI	-0.310***	-0.375***			-0.335***	
	(0.061)	(0.058)			(0.050)	
CCI			-4.664***	-5.217***		-5.268***
			(0.836)	(0.719)		(0.639)
EthnicF		13.335***		16.505***		
		(2.945)		(3.020)		
Primary	-0.094**	-0.036	-0.054	0.006	-0.066**	-0.018
	(0.037)	(0.034)	(0.043)	(0.040)	(0.028)	(0.032)
Secondary	0.066**	0.118***	0.052	0.118***	0.000	-0.015
	(0.028)	(0.027)	(0.033)	(0.033)	(0.028)	(0.033)
Openness	-0.006	0.063***	-0.000	0.090***	-0.034***	-0.029***
	(0.010)	(0.020)	(0.011)	(0.022)	(0.008)	(0.010)
Government	0.412***	0.322***	0.378***	0.269***	0.539***	0.500***
	(0.077)	(0.074)	(0.092)	(0.089)	(0.080)	(0.082)
Natural	0.070	-0.118**	0.060	-0.183***	0.059	0.050
	(0.045)	(0.052)	(0.046)	(0.059)	(0.043)	(0.045)
GDP	-5.944***	-5.494***	-6.350***	-5.574***	-5.085***	-5.614***
	(0.464)	(0.426)	(0.484)	(0.430)	(0.434)	(0.449)
MinWage	-0.001	0.004	-0.009	-0.002	0.008	-0.000
	(0.006)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)
Informal	-0.055***	-0.106***	-0.035*	-0.098***	-0.013	0.007
	(0.018)	(0.024)	(0.021)	(0.025)	(0.013)	(0.016)
Constant	110.890***	102.181***	98.606***	81.567***	106.147***	93.826***
	(6.031)	(5.676)	(4.144)	(4.871)	(5.522)	(3.917)
Observations	249	249	215	215	249	215
R-squared	0.294	0.341	0.207	0.321	0.508	0.419

Notes: This table shows six different models to estimate the effect of corruption on income inequality. All models were estimated using the IV technique. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.
Columns (1), (2) and (5) use the BCI as corruption measure; columns (3), (4) and (6) use the more traditional CCI. Columns (1), (3), (5) and (6) instrument corruption with settlers mortality and democracy index; columns (2) and (4) instrument corruption and ethnic fictionalization indexes with settlers mortality, democracy and latitude. Columns (1) to (4) use the Net Gini index as dependent variable; columns (5) and (6) use the Market Gini Index. All models passed the specification tests provided (see Table 4).

Table 4: Corruption effect on income inequality (Table 3 tests)

	Net Gini				Market Gini	
TESTS	(1)	(2)	(3)	(4)	(5)	(6)
Wooldridge robust score	10.82	11.76	9.30	9.16	5.43	6.89
(p-value)	(p = 0.00)	(p = 0.00)	(p = 0.00)	(p = 0.01)	(p = 0.02)	(p = 0.01)
Robust regression-based test	35.94	18.35	44.82	16.59	11.42	25.2
(p-value)	(p = 0.00)	(p = 0.00)	(p = 0.00)	(p = 0.00)	(p = 0.00)	(p = 0.00)
First stage R-sq.	0.3		0.39		0.3	0.39
First stage prob >F	0.00		0.00		0.00	0.00
Shea's partial R-sq (BCI)		0.13		0.13		
Shea's partial R-sq (EthnicF)		0.34		0.28		

Notes: This table shows specification tests of the six models in Eqn. 3. The *Wooldridge robust score* and the *Robust regression-based test* show that the relationship between corruption and income inequality should indeed be treated as endogenous. The *First stage R-sq*, *First stage Prob > F* and *Shea's partial R-sq* argue in favor of the relevance of the instruments used. All the models passed all the tests.

Table 5: Income inequality effect on corruption

	BCI		CCI	
VARIABLES	(1)	(2)	(3)	(4)
NetGini	0.955***		0.084***	
	(0.311)		(0.018)	
MarketGini		1.451**		0.112***
		(0.645)		(0.036)
Openness	0.012	0.034	-0.002	0.000
	(0.034)	(0.045)	(0.002)	(0.003)
Primary	0.182	0.251	0.012*	0.013
	(0.136)	(0.205)	(0.007)	(0.009)
Secondary	0.345**	0.499**	0.019**	0.033***
	(0.138)	(0.204)	(0.008)	(0.013)
Government	-0.335	-0.811*	-0.044**	-0.080***
	(0.277)	(0.479)	(0.017)	(0.027)
Natural	-0.532**	-0.675**	-0.038**	-0.048**
	(0.244)	(0.315)	(0.015)	(0.019)
EconomicF	-0.504***	-0.515***	-0.033***	-0.035***
	(0.139)	(0.176)	(0.009)	(0.011)
Democracy	0.676	-3.500		
	(1.736)	(2.902)		
Transparency	-0.585***	-0.702***	-0.061***	-0.074***
	(0.180)	(0.254)	(0.011)	(0.016)
Orientation	0.360	0.594	-0.112	-0.118
	(1.262)	(1.657)	(0.081)	(0.102)
Constant	67.110***	50.970	2.418**	1.782
	(20.459)	(33.449)	(1.158)	(1.741)
Observations	58	58	44	44
R-squared	0.576	0.300	0.772	0.629

Notes: This table shows four different models to estimate the effect of income inequality on corruption. All models were estimated using the IV technique. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Columns (1) and (3) use the Net Gini index as inequality measure; columns (2) and (4) use the Market Gini index. All columns instrument inequality with the proportion of ‘mature’ population (40 to 59 years) with respect to the total adult population (15 to 69 years). Columns (1) and (2) use the BCI as dependent variable; columns (3) and (4) use the CCI. All models passed the specification tests provided (see Table 6).

Table 6: Income inequality effect on corruption (Table 5 tests)

TESTS	BCI (1)	BCI (2)	CCI (3)	CCI (4)
Wooldridge robust score	5.61	10.03	4.65	11.25
(p-value)	(p = 0.02)	(p = 0.00)	(p = 0.03)	(p = 0.00)
Robust regression-based test	4.72	9.50	4.7	12.1
(p-value)	(p = 0.03)	(p = 0.00)	(p = 0.04)	(p = 0.00)
First stage R-sq.	0.66	0.48	0.66	0.51
First stage prob >F	0.00	0.00	0.00	0.00

Notes: This table shows specification tests of the six models in Eqn. 5. The *Wooldridge robust score* and the *Robust regression-based test* show that the relationship between corruption and income inequality should indeed be treated as endogenous. The *First stage R-sq* and *First stage Prob* $>$ *F* argue in favor of the relevance of the instruments used. All the models passed all the tests.

List of Figures

Figure 1: Average corruption in Latin America (2005-2015).

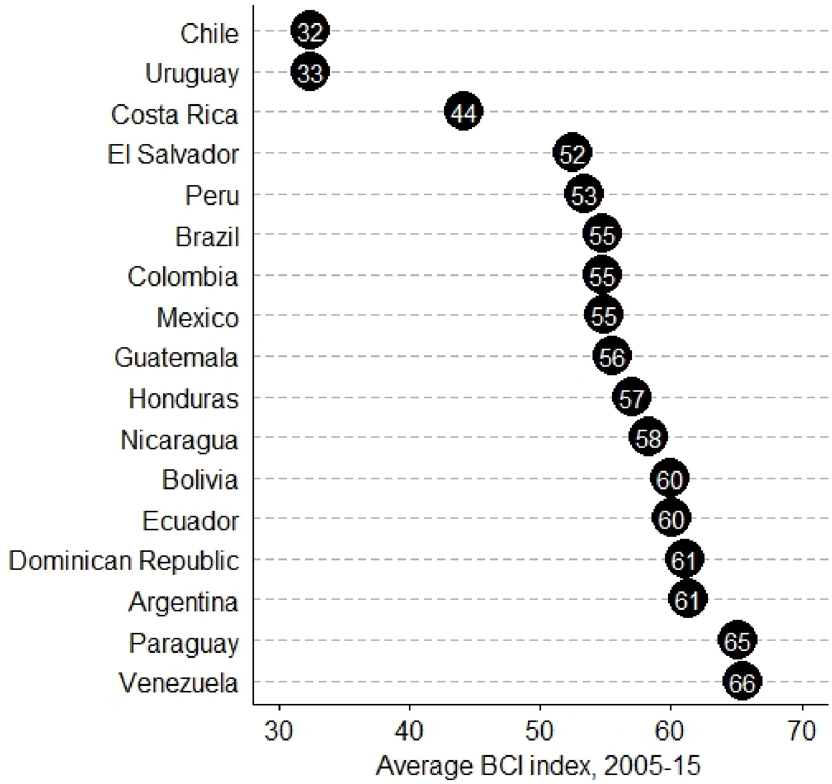

Figure 2: Average inequality in Latin America (2005-2015).