Who really benefits from corruption? The effects of corruption on income distribution in Latin America[1]

Abstract

This paper contributed to better understanding a counterintuitive, yet empirically solid, finding of recent research on Latin America: that increases in corruption have been accompanied by reductions in income inequality. By using Bayesian estimates of corruption perception suitable for panel estimations, and by identifying previously ignored meaningful differences in the typologies of corruption, we show that this effect has been driven by the consistent use of perception surveys as a proxy to measure corruption. Once detailed, experienced-based measures of corruption are used, the marginal impact of corruption on inequality is negative when it provides of informal labor market opportunities to the general public, but positive when firms gain access to privilege treatments. By correcting measurement errors from previous fixed-effect estimations, our results show that general public-level corruption tends to increase the share of income for the bottom 20%, while firm-level corruption tends to increase the share of the top 10%. Our results indicate a pressing need to develop a more precise picture of how corruption and inequality interact, and to define how corruption may create different distributional effects depending on who is allowed to violate the law to obtain economic and legal privileges.

Key words - Latin America, corruption, income inequality, informal markets, marginal effects, panel data

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Governmental corruption is an undeniably important area of interest for political scientists, but although the subject has long been subject to empirical scrutiny, the relationship between corruption and economic inequality remains enigmatic. Largely, this is due to an unresolved schism in the literature between scholars who observed that inequality increases as corruption increases, and those who found that inequality decreases as corruption increases, conditional on the presence of informal markets and other regional variables. But the opaqueness of this issue is also in part due to past methodological deficiencies.

The prevailing 'common sense' view, that economic inequality increases as corruption increases, has been borne out by studies that have identified a positive effect of corruption on income inequality (Li et al., 2000; Gyimah-Brempong & de Munoz, 2006; Dincer & Gunalp, 2012; Dong & Torgler, 2013). However, mounting evidence has shown that, in Latin America, increases in corruption tend to be associated with reductions in income inequality (Dobson & Ramlogan-Dobson, 2012). Furthermore, these results are robust and have been corroborated by different studies (Dobson & Ramlogan-Dobson, 2010; Andres & Ramlogan-Dobson, 2011).

According to current research, the discrepancy in the literature may be explained by the interaction of corruption with vote-buying (Wong, 2016), and the presence of large informal markets (Dobson & Ramlogan-Dobson, 2010)[2]. Corruption spurs resource distribution due to clientelist linkages that come from vote-buying (Wong, 2016; Holland, 2016). Also, corruption spurs an informal market in which less well-off individuals can more readily participate and more easily become economically productive. This is the case because corruption reduces the costs to participate in informal markets by providing of a second-best alternative to regulatory barriers to entry (Dobson & Ramlogan-Dobson, 2012).

Despite this recent insight, past methodological deficiencies still muddy the issue. In particular, past research has suffered from poor measurement assumptions. Most studies have relied

[2]A relationship between corruption and informal sectors has already been demonstrated in the area of public debt: the existence of large informal markets magnifies the positive effect of corruption on public debt, acting as complements (Cooray et al., 2017).

on measurements that merely capture the perception of corruption, a measure that research has increasingly identified as weakly correlated with the existence of real acts of corruption (Donchev & Ujhelyi, 2014; Razafindrakoto & Roubaud, 2010; Treisman, 2007; Abramo, 2008). Furthermore, corruption perception series are not suitable for panel studies, given their abundant methodological changes over time (Treisman, 2007). Corruption has also been commonly assumed to be a monolithic illegal behavior that affects society in general. This ignores a large body of literature which has shown that how corruption is organized and who gets affected by it are among the most meaningful variables needed to identify its impacts (Shleifer & Vishny, 1993; Heidenheimer, 2002; Johnston, 2005; Nyblade & Reed, 2008; Olken & Barron, 2009; Banerjee et al., 2012).

Given that economic inequality is fast becoming the defining issue of our time, and that sweeping anti-corruption efforts are gaining momentum around Latin America, there is a pressing need to develop a more precise picture of when and how these forces interact. By distinguishing among types of corruption, our paper elucidates the conditions under which corruption may reduce economic inequality, and those under which it may not. Our main contribution is that we bridge both sides of the debate by accessing better and more nuanced measures of corruption, ones that allow us to differentiate between corruption that affects the general public and corruption that affects firms.

We accomplished this by relying on Bayesian perception estimates of corruption suitable for panel studies, and on extensive records of reported acts of corruption. This enabled us to develop mixed-effect estimates which show that corruption reduces inequality when it targets the general public, but increases it when it targets firms. In line with differentiated distributional outcomes, we show that corruption affecting the general public tends to increase the share of income for the bottom 20%, while corruption affecting firms tends to increase the income of the top 10%. We attribute these results to the distinct ways in which economic and legal privileges are distributed when corruption affects individuals, as opposed to capital owners.

The rest of the paper is structured as follows. The first section gives an account of the most

recent findings in the literature regarding the corruption and economic inequality debate. The second section describes the exceptional datasets that made this research possible. The third section presents our identification strategy. The fourth section presents results and robustness tests that employ different measures of corruption, different approaches to measure income distribution, and different identification strategies. We then conclude by providing a summary of our findings and avenues for future research.

The distributional effects of corruption

The inequality compounding economic effects of corruption have been well documented. Research has shown that corruption generates a tax system which disproportionately favors affluent individuals, creates judicial systems where only the corrupt find it easier to become rich (Glaeser et al., 2003), diverts government spending away from public programs (Chetwynd et al., 2003), limits economic growth through the inefficient use of public spending (dAgostino et al., 2016), allows bureaucrats to conspire with the rich (Blackburn & Forgues-Puccio, 2007), generates extra-normal rents for incumbent entrepreneurs (Foellmi & Oechslin, 2007), redistributes income towards the wealthy (Dong & Torgler, 2013), makes foreign aid more regressive (Pham, 2015), and concentrates public funds in the hands of elites (Wong, 2016). Additionally, a study of government officials convicted for crimes related to corruption shows that this measure is also correlated with larger income inequality (Dincer & Gunalp, 2012). Overall, there is a wealth of evidence supporting the traditional view, that we should expect corruption to exacerbate economic inequality.

Despite this, the literature has also shown that corruption may promote economic growth under certain circumstances. These are such that grant vulnerable populations access to income sources outside of the formal regulated market. Corruption is here conceived as a second-best substitute to rule of law (Huntington, 1968; Leff, 1964) that allows citizens to evade burdensome regulations (Osterfeld, 1992), and creates economic opportunities for individuals unable to pay the high cost

of operating in complete compliance with the rules of the formal economy (Sarte, 2000; Méon & Sekkat, 2005; Méon & Weill, 2010).

Furthermore, most evidence of the possible economic benefits of corruption comes from global instances of poor governance. Scholars have found that corruption has no significant effect on economic growth in democracies, but inflicts significant economic harm in non-democracies (Drury et al., 2006). Additionally, that corruption may help expand production outputs in countries with shoddy institutions (Houston, 2007), inept governance (Aidt et al., 2008), and less political stability (Shabbir et al., 2016). Moreover, corruption results in increased trade in countries with high tariffs (Dutt & Traca, 2010), and facilitates investment and productivity in countries lacking a decent system of property rights (De Vaal & Ebben, 2011). Most of the recent research validates the idea that increased corruption raises the economic growth rate in an inverted U-shaped way. This holds because, in very corrupt environments where regulations are burdensome and rule of law absent, marginal increases in corruption allow some degree of production to happen (Ahmad et al., 2012).

Current literature examining the case of Latin America in particular has also found an empirically solid, negative relationship between income inequality and corruption (Andres & Ramlogan-Dobson, 2011; Dobson & Ramlogan-Dobson, 2010, 2012; Wong, 2016). According to these studies, corruption allows informal labor markets to thrive by providing opportunities for less well-off workers lacking the productivity needed to remain profitable in the formal economy (Dobson & Ramlogan-Dobson, 2012). Electoral politics, in this case, have also been found to be relevant. When corruption takes the form of cheating (vote-buying), it may reduce inequality because it involves resource distribution and the building of clientelist linkages (Wong, 2016). The puzzling nature of the redistributive effects of corruption in Latin America is at the frontline of research on the topic, as it has been alarming to policy makers and disconcerting to academics.

Although the empirically-driven literature summarized above is extensive, it has so far failed to capture the nuanced differences between types of corruption, a theoretical proposition that predicts interesting heterogeneous effects. All previous research has tacitly operated under the assumption

that corruption is a monolithic illegal activity, and that the perception of corruption is an accurate measure of real corruption. This is far from acceptable.

Corruption in fact encompasses many different illegal practices that may have very distinct distributional effects. The seminal work of Johnston (2005) is well known for identifying the existence of different corruption syndromes, and for prompting academics to use broader, systemic definitions of corruption typologies. According to Johnston (2005), scholars should consider how the public and private domains were defined, the features of the boundaries between wealth and power, and who benefited. Other scholars have also pointed out that corruption can take the form of looting or cheating (Nyblade & Reed, 2008), can be an act of leadership or followership depending on dominant conceptions of power (Heidenheimer, 2002), can have different forms of network organization (Olken & Barron, 2009; Shleifer & Vishny, 1993), can differ depending on agents relative ability to pay and objects' values (Banerjee et al., 2012), or can just be a set of different pathologies that depend on the interaction between governments and citizens (Rose-Ackerman & Palifka, 2016).

Indeed, most recent research points to heterogeneous effects conditional on how well-organized corruption is. Blackburn & Forgues-Puccio (2009) show that organized corruption allows for more innovation and growth than disorganized networks. This is because centralized corruption removes any uncertainty, so producers know whom to bribe to further their interests. Otherwise, in a decentralized system of corruption, economic agents do not know whether their bribe will be effective (De Vaal & Ebben, 2011). Interestingly, most of the literature that has tried to solve the paradox of rapid growth and prevalent corruption in some East Asian countries has concluded that some forms of corruption are more functional than others, depending on its degree of centralized organization (Rock & Bonnett, 2004; Rothstein, 2015; Rothstein & Torsello, 2014; Wedeman, 2012)

To the extent of our knowledge, until now the literature has only analyzed the distributional effects of corruption by measuring the perception of it. This is problematic because these subjective assessments are seldom correlated with real corruption levels (Svensson, 2005; Treisman, 2007;

Abramo, 2008; Donchev & Ujhelyi, 2014; Standaert, 2015). In Mexico, Morris (2008) found no relationship between actual corruption and perceptions of corruption. In Indonesia, Olken (2009) showed that an increase of 10% in experienced corruption increases the perception of corruption only by 0.8%. In Russia, Rose & Mishler (2010) found evidence that perceptions of the prevalence of corruption were almost completely unrelated to the actual experience of it. For instance, while 89% of Russians thought that most police officers were corrupt, only 5% had experienced paying a bribe. In Africa, (Razafindrakoto & Roubaud, 2010) surveyed experts and residents from different countries and found that experts grossly overestimated the extent of corruption that residents reported. Lastly, a cross-country study of 60 cases showed that, for most of them, the perception of corruption did not explain experiences of corruption, and that opinions instead just followed the trend of other opinions (Abramo, 2008).

Furthermore, there's solid evidence that different variables explain the existence of the perception of corruption, as opposed to actual corruption. Individuals tend to perceive more corruption in low income authoritarian countries that are closed to trade, depend on fuel exports, have fewer women in government positions, and have heavy regulations or unpredictable inflation (Treisman, 2007). However, having women in government positions, authoritarianism, and inflation have all not been found to explain real levels of corruption (Treisman, 2007). More recently, (Donchev & Ujhelyi, 2014) have shown that some of the factors commonly thought to reduce corruption, such as economic development, democratic institutions, and Protestant traditions, systematically reduce the perception of corruption, but not actual corruption. This indicates that perception indices are influenced by absolute (as opposed to relative) levels of corruption (Donchev & Ujhelyi, 2014).

Although the literature on corruption is extensive, what studies using perception indices are actually measuring remains unclear. It is also difficult to tell whether perceptions could possibly be compared across countries (Banerjee et al., 2012; Knack, 2006; Rose-Ackerman, 1999), particularly because perception-based measures are influenced by how many corrupt transactions people can

realistically see (Bardhan, 2006). Thus, it is reasonable to think that petty, day-to-day corruption may be more visible than more serious corruption among elites. This would also imply that past research may have not accurately captured the features, extent, or effects of corruption, and that much must be done to improve the measurements and assumptions behind corruption research. We will describe our data and explain our empirical strategy to overcome these deficiencies in the next two sections.

Data

The measures of corruption most commonly used in the literature are the Corruption Control Index (CCI), available every other year since 1996, the Corruption Perception Index (CPI), available yearly since 1995, and the International Country Risk Guide (ICRG), issued by the Political Risk Services company and available monthly for each year since 1980. The first two are perception-based measures composed of aggregated data from different sources, such as surveys of local and international business experts and risk ratings made by private firms. The last one is a corruption rating based on the opinion of experts consulted by the Political Risk Service. Both the CCI and the CPI are free to use, but the ICRG is not.

All three of these measures have substantial flaws. Both the CCI and CPI have been criticized as unsuitable for longitudinal analyzes (Treisman, 2007; Hawken & Munck, 2011; Standaert, 2015). Also, the methodology used to create the CPI has changed several times over the years, and this means that changes in methodology may be the omitted variable driving changes in corruption levels. This problem is accentuated, for both the CPI an CCI, because sources and informants are sometimes different from year to year. This implies that interpreting changes in successive years could be quite problematic, unless we assume that the underlying parameters of these two different samples are equivalent [3]. Finally, in the case of ICRG, there is seldom any transparency as to

[3]See the work of Arndt & Oman (2006), Knack (2007) and for some interesting evaluations of inconsistencies

how the ratings attributed to different countries are comparable (Treisman, 2007). There have also been several instances of data recalibration that have caused unexplained leaps in ratings in a matter of months. Despite these issues, the use of the CCI, the CPI, and the ICRG has been broadly accepted by the literature, due to the lack of alternatives.

Instead of relying on the CCI, CPI, or ICRG to measure our main explanatory variable, we use the Bayesian Corruption Indicator (BCI) that aims to correct the problems of other measures by using a state-space model (Standaert, 2015). The BCI was very recently developed by the Study Hive for Economic Research and Public Policy Analysis (SHERPPA) at Ghent University. It relies on a Bayesian Gibbs sampling algorithm and corrects for missing values, allowing the model to be estimated without additional manipulations or assumptions. The result is an unbiased indicator that is methodologically more solid than the CPI and allows for comparisons over time[4]. Our goal is to replicate previous findings in the literature using more refined data processing techniques that improve our ability to assemble corruption perception data suitable for panel estimations. Despite its relative novelty, use of the BCI in empirical studies has been growing (Ouattara & Standaert, 2017; Ferrali, 2017).

In addition to Bayesian-corrected measures, this paper also takes advantage of the newest methods for measuring experiences of corruption (rather than perceptions) in more nuanced ways. These newer methods have been developed to give more concrete measures of corruption. They accomplish this by refining survey and data collection techniques that improve the ability to assemble data on self-reported bribes for two main categories: bribes extracted from ordinary citizens and bribes paid by firms[5]. Academics had so far ignored these measures, due to the limited number of time periods available for study. Fortunately, as of now, these measures have

[4]All models presented in this paper were also tested using the CCI. We selected the CCI over the CPI and the ICRG due to its recognized methodological advantages (Treisman, 2007; Standaert, 2015). Whenever using CCI, it was multiplied by -1 such that, as with BCI, a higher value always refers to higher levels of corruption.

[5]Transparency Internationals Global Corruption Barometer (GCB) Survey exemplifies the first type, and has been used in several previous empirical studies (Rose-Ackerman & Palifka, 2016; Treisman, 2007; Ivanyna & Shah, 2011). Another example of the first type comes from a cross-national survey conducted by the United Nations Interregional Crime and Justice Research Institute (UNICRI) in the late 1990s.

accumulated enough observations to make them empirically feasible to work with[6].

We measure general public's corruption with an experience-based indicator obtained from the GCB. The GCB is the only cross-national public opinion survey measuring direct experiences with corruption by the general public (Global Corruption Barometer, 2013). This longitudinal survey has been conducted 7 times between 2004 and 2013. Data for 125 countries is available, but, on average, each country has observations for only 4 years. Thus, we focused on the most commonly asked question: In the past 12 months, have you or anyone living in your household paid a bribe in any form? (sic). This measure has previously been used in published research papers like (Rose-Ackerman & Palifka, 2016; Treisman, 2007; Ivanyna & Shah, 2011). Throughout the paper we will refer to this measure simply as *GCB*.

We measure firms' corruption with an experience-based indicator obtained from the Enterprise Surveys (ES) developed by the World Bank. The name assigned to it in the aggregated ES results is Bribery Incidence. It captures the percentage of firms that report they have experienced at least one bribe payment request during six transactions dealing with utilities access, permits, licenses, and taxes. Firms are representative by size and geography[7]. For Latin America, we have data for 2006 and 2010. This measure has previously been used in published research papers like (Yamarik & Redmon, 2017; Ivanyna & Shah, 2011). We will refer to it as *ES*.

Our main dependent variable, inequality, is measured using the 6th 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 both primary sources, like the Latin American and Caribbean Socioeconomic Database (SEDLAC) and the Luxembourg Income Study Database (LIS), and secondary sources, like the All The Ginis Dataset of the World Bank. Im-

[6]The importance of distinguishing between these two types of corruption is already evident in the way in which its actors are affected by corruption. As the general public often rely heavily on public services, they are more passively related to corrupt street-level bureaucrats (Justesen & Bjørnskov, 2014) while firms are more likely to adopt a set of bribery best practices as a routine, being themselves active perpetrators of bribery (Ufere et al., 2012).

[7]Data comes from small (5-19 workers), medium (20-99), and large (100+) companies in the largest cities in each country

putation of missing data allows the SWIID to have the greatest coverage of Gini indices in both time and space (Ferreira et al., 2015). SWIID also maximizes comparability and is better suited to longitudinal panel analysis than any other measure (Solt, 2016). The most recent published paper analyzing the effects of corruption on inequality rely on this measure (Pedauga et al., 2017).

Our models employ several control variables that have been regularly used in the literature on corruption and inequality (Pedauga et al., 2017; Dobson & Ramlogan-Dobson, 2012; Andres & Ramlogan-Dobson, 2011; Gupta et al., 2002; Gyimah-Brempong, 2002). These are the size of the informal sector, degree of openness in the economy, GDP per capita, national income from natural resources, government consumption, the educational attainment in the country (measured as the percentage of the population over 15 years old with primary or secondary education), the income share held by the richest 10% and the poorest 20%, and indices that are proxies for the strength of democratic institutions.

The size of the informal sector from 1999 to 2013, *informal*, was estimated following the dataset in Hassan & Schneider (2016). In their analysis of the effects of corruption on inequality, Dobson & Ramlogan-Dobson (2012) had already used this dataset, but for a much more limited time frame [8].

Following Dobson & Ramlogan-Dobson (2012), we include measures of primary and secondary schooling. We define *primary* and *secondary* as the population over 15 years old with either primary or secondary education. This data was obtained from the widely used Barro-Lee dataset available at the World Bank. For the *minWage* variable, we obtain data from a minimum wage index constructed by CEPALSTAT, as used in Cornia (2013).

Finally, we measured the rest of the controls using the World Bank's World Development Indicators. To create a proxy for the openness of the economy, we specified *openness* as the sum of exports and imports in relation to GDP. The proxy *GDP* was the natural logarithm of GDP per

[8] Other studies have measured informality using data from the SEDLAC. We decided not to use SEDLAC because it has significantly fewer observations, affecting sample size.

Table 1: Summary Statistics

VARIABLES	N	MEAN	SD	MIN	MAX
ES	90	10.62	6.644	1.300	31.50
GCB	113	16.69	9.957	3	43
BCI	558	52.28	8.390	30.36	68.31
CCI	306	0.308	0.686	-1.573	1.444
GINI	555	47.02	4.589	32.73	57.68
POOR	331	3.546	0.966	0.800	6.100
RICH	331	39.63	4.608	23	51.20
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
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
INFORMAL	255	43.98	16.00	17.75	81.45

capita. *Natural* was the percentage of GDP that was income from natural resources. *Government* was government consumption as a percentage of GDP. *Poor* was the share of income held by the poorest 20% of the population, and *rich* was the share of income held by the top 10%. *Poor* and *Rich* were used as alternative dependent variables.

Descriptive statistics of each of the variables included in our empirical testing can be found in Table 1. Our database included 18 countries from Latin America (17 from the GCB) and spanned the years between 1999 and 2013 [9] When a country had missing data between two consecutive years, we imputed values using a linear function.

[9] Additional years are available for perception-based measures: CCI (1996 2013), BCI (1984 2013). Experience-based measures have less observations: GCB (2004-2013), and ES (2006-2010).

Empirical Strategy

We test the relationship between inequality and corruption using three econometric specifications: Generalized Latent and Mixed Model (GLLAMM), Instrumental Variables Model (IV), and Fixed-Effects (FE). Unlike past research, we use measures of corruption perception as well as experienced corruption. Our study is also unique because we divided experience with corruption into two types: corruption that affects the general public and corruption that affects firms. In this section, we describe the logic and validity of each of our specifications.

We first tested the relationship between inequality and corruption using a Generalized Latent and Mixed Model (GLLAMM). This model is recommended for our research because it allows us to correct for changes in the variance of inequality measurement errors over time. We expect inequality measurement errors to change over time because country offices attempt to improve the quality of their income survey instruments every year (Pedauga et al., 2017). As a result, this could lead us to find phantom reductions in inequality, although true income inequality remained unchanged[10]. If not corrected, inequality measurement errors could result in panel regressions with inconsistent estimates (Ronning & Schneeweiss, 2011). As Rabe-Hesketh et al. (2003) have explained, considering measurement errors is crucial to eliminate biases from the estimates of the regression parameters, and to facilitate the prediction of the true covariate, or exposure for an individual unit. This method has been used by Pedauga et al. (2017) with the same purpose.

The general structure of the GLLAMM model is:

$$d_{i,t} = D_{i,t} + \eta_{i,t}$$

$$\eta_{i,t} \sim N(0, \sigma_{\varepsilon}^2)$$

$$d_{i,t} = \beta_0 + \beta_1 C_{i,t} + \beta_3 X_{i,t} + \eta_{i,t}$$

[10]Indeed, in our measure of inequality (Gini in the SWIID) Solt (2016) argues that long errors are virtually eradicated, yet the presence of minor errors remains inevitable.

where the subscript i represents the country and t the year. C represents the experienced corruption measure to be used (a higher value represents greater corruption). In this model, we assume that our measure of inequality, d, is only a proxy for true inequality, D. Our measure for year t and the Latin American country i differs from $D_{i,t}$ by a measurement error $\eta_{i,t}$ which is normally distributed. X is a vector of covariates. We assume a linear relationship between inequality and corruption.

As mentioned in the Data section, our preferred tools for measuring perceived corruption and inequality are the BCI and the Net Gini, respectively. Hence, our main estimations will have the Net Gini coefficient as a dependent variable and the BCI index as the main independent variable.

We included controls for economic variables that could also influence inequality, like trade openness and GDP per capita. The openness of the economy is suspect because increased openness may encourage the export sectors, such as manufacturing, to hire more workers, and this might reduce inequality (Cornia, 2010). This is consistent with papers developed by Dobson & Ramlogan-Dobson (2012) and Pedauga et al. (2017). Furthermore, we avoid having the indicator of corruption reflect the effect of economic development by adding GDP per capita as a control in all specifications [11]. We expect that the higher the GDP per capita is, the lower inequality will be (Dobson & Ramlogan-Dobson, 2012).

We also included controls for variables that had been proven to impact inequality, like dependence on natural resources, the size of the government, education, and minimum wages. A high dependence on natural resources leads to greater inequality because it encourages the intense concentration of property and the income it generates (Haass & Ottmann, 2017; Tornell & Lane, 1999; Gupta et al., 2002). Large governments can reduce inequality through larger expenditures that provide more public goods and services or social welfare programs. Thus, we expect that the greater the government expenditure is, the lower inequality will be (Gyimah-Brempong, 2002;

[11] Economic development can be directly related to corruption at least through the increasing use of mobile phones that, according to Kanyam et al. (2017), are a powerful tool to reduce corruption. We must avoid confusing the effect of economic prosperity and corruption.

Li et al., 2000). According to Dobson & Ramlogan-Dobson (2012), it is expected that secondary education tends to reduce inequality, while primary education does not. Ergo, we expect a higher minimum wage to have a reducing effect on the Gini index (Cornia, 2013). To our knowledge, no other study analyzing the effects of corruption on inequality has used minimum wage as a control variable.

Finally, all our models include a measure of the size of the informal sector, one of the main variables explaining the apparent negative relationship between corruption and inequality (Dobson & Ramlogan-Dobson, 2012, 2010; Andres & Ramlogan-Dobson, 2011). Informal markets provide sources of income to vulnerable individuals that are not productive enough to take part in formal labor markets (Chong & Calderon, 2000). This means that when anti-corruption polices crackdown on informal markets the income of the poorest participants is affected the most. Therefore, we expect that informal markets tend to reduce inequality, but more importantly, that the effect of corruption will lose significance by controlling for the size of the informal sector.

Several studies point to problems of endogeneity in trying to estimate the effect of corruption on inequality (Li et al., 2000; Gyimah-Brempong, 2002; Gupta et al., 2002; Gyimah-Brempong & de Munoz, 2006; Dobson & Ramlogan-Dobson, 2012). Therefore, in addition to our GLLAMM models, we used an IV model to test for the relationship between corruption and inequality.

The general structure of the 2SLS model was:

$$C_{i,t} = \alpha_0 + \alpha_1 Dem_{i,t} + \alpha_2 SM_i + \theta_{i,t}$$

$$D_{i,t} = \beta_0 + \beta_1 C_{i,t} + \beta_2 X_{i,t} + \zeta_{i,t}$$

In the first stage, we estimate the linear relationship between corruption ($C_{i,t}$), democracy ($Dem_{i,t}$), and the natural logarithm of the mortality rate faced by European settlers (SM_i) with an error $\theta_{i,t}$. The second stage estimates the effect of corruption on inequality with the same vector of covariates X as in the GLLAMM estimates and an error ζ.

We are confident of the instruments used in the first stage, because much published research has used democracy (Gupta et al., 2002; Dobson & Ramlogan-Dobson, 2012) and settler mortality (Dobson & Ramlogan-Dobson, 2012; Gyimah-Brempong, 2002; Gyimah-Brempong & de Munoz, 2006) as instruments for corruption perception.

Our first instrument, Democracy, was measured using a dichotomous index of democracy, as created by Acemoglu et al. (in press)[12]. The reason is that most popular democracy indices, such as those expanded by Freedom House and Polity IV, have a high level of measurement error (Acemoglu et al., in press). The used measure combines information from various sources. In a given year, a country is considered democratic if Freedom House classifies it as 'Free' or 'Partially Free,' and if Polity IV assigns it a positive rating. When a country did not have a rating from either Freedom House or Polity IV, classifications by Cheibub et al. (2010) or in Boix et al. (2013) are taken into consideration. This variable was developed to cover the period between 1970 and 2010. For the purposes of this paper, we updated the variable to include the years up to 2015. In 1970, only a third of Latin American countries were democratic, but by 1990 only three were not (Mexico, Panama and Paraguay). By 2015, finally, all were democratic. As can be seen in the case of Mexico, having a declared dictator is not necessary for the index constructed in Acemoglu et al. (in press) to consider a country undemocratic.

Our second instrument, the natural logarithm of the mortality rate faced by European settlers, was extracted from the dataset in Acemoglu et al. (2001). This measure is ideal for Latin America because we have data for each of our 18 countries. This data shows that Nicaragua and Panama have the highest mortality rates, while Argentina and Chile have the lowest.

Variables used as instruments should meet two requirements. First, they should be correlated with the endogenous explanatory variable, in this case, corruption. And second, they should be

[12]Research shows that democracy has a reducing effect on corruption only in economies that have already crossed a level of GDP per capita of approximately US$2,000 (in 2005 US$) (Jetter et al., 2015). In Latin America only Nicaragua, Honduras, Bolivia and Paraguay are below this threshold, so we can expect that better democratic institutions are related to less corruption.

uncorrelated with the error term in the main equation. We benefit from our model being overidentified (two instruments and one endogenous regressor), allowing us to test both our requirements with the Sargan (1958) and Basmann (1960) chi2 tests. If we reject both tests, then it is likely that our instruments are uncorrelated with the error term, and that our model is correctly specified. Indeed, our final IV model rejected both tests (see columns 5 and 6, Table 2).

If corruption actually is exogenous, then it would be worthwhile to exchange the IV estimator for a OLS estimator because it would be more efficient. We use Durbin (1954) chi2 and Wu-Hausman (Wu, 1974; Hausman, 1978) F tests to check if an IV estimator is needed. The IV technique is worth using only if both tests are significant, and our final IV model specification rejected both (see columns 5 and 6, Table 2).

We also tested the weakness of our instruments using the Cragg & Donald (1993) minimum eigenvalue statistic. Stock & Yogo (2005) defined instruments as weak if a Wald test at the 5% level has a rejection rate of no more than 10%, 15%, 20%, or 25%. We feel comfortable using a rejection rate of 15% at most. Therefore, we conclude our instruments are not weak if our Cragg and Donald statistic exceeds 11.59, which is the critical value at the 15% rejection rate. Our final IV model specification rejected the possibility that we are using weak instruments (see columns 5 and 6, Table 2). Given the outcomes of these tests, we are confident in our results.

Instrumental Variable Models specifications cannot be used for experience-based corruption measures that have been divided by type. We have two types of experience-based corruption measures, one for the general public and one for firms. Thus, for these variables we will perform robustness checks with an additional identification using a FE estimator. Doing so will also account for the idiosyncratic characteristics of each country. This specification has been used in published research, for example Pedauga et al. (2017).

The general structure of the FE model is:

$$D_{i,t} = \beta_0 + \beta_1 C_{i,t} + \beta_2 X_{i,t} + u_i + \varepsilon_{i,t}$$

where the subscript i represents the country and t the year. u_i captures the unobserved characteristics of the country and $\varepsilon_{i,t}$ is the error term. D represents the measure of inequality (a higher value represents greater inequality), C the experienced corruption measure to be used (a higher value represents greater corruption), and X is the same vector of covariates used in the GLLAMM models. β_1 represents the coefficient of the measure of corruption, and β_2 is a vector of coefficients.

Results

Table 2 presents the GLLAMM and IV results for the effect of perceived corruption on income inequality. GLLAMM specifications are used in columns 1 to 3, while IV's are used in columns 4 to 6. Columns 1,2,4, and 5 use the Bayesian estimate of corruption, BCI, as corruption measure. The rest use the more traditional CCI as a robustness check.

Focusing on the GLLAMM models, column 1 indicates that, even without informal markets as a control variable, corruption seems to have an equalizing effect on income inequality in Latin America: the more points on the BCI, the smaller the Net Gini index. This is consistent with the most recent empirical findings (Dobson & Ramlogan-Dobson, 2012)[13]. Column 2 confirms the negative coefficient of corruption when informality is included in the model as a control. A one unit rise in the BCI is associated with a decrease of 0.045 units in the net income Gini index. Column 3 confirms that this result is solid, even without our Bayesian estimate of corruption. When using the CCI, this effect is even more pronounced.

With respect to IV models, the equalizing effect of corruption is maintained in all three columns. A one unit increase in the BCI leads to a 0.31 decrease in the net income Gini index (see column 5). This effect is almost seven times stronger than the one estimated using the GLLAMM model, indicating that not accounting for the endogeneity problem can underestimate the actual effect.

[13] A recent paper published by Pedauga et al. (2017) reported results that go in the opposite direction, but this is because the authors misinterpreted the direction of the CCI index. This mistake is common because CCI has positive values for less corrupt countries.

Table 2: Corruption perceptions and inequality

	(1)MM	(2)MM	(3)MM	(4)IV	(5)IV	(6)IV
BCI	-0.115***	-0.045***		-0.068	-0.310***	
	(0.014)	(0.015)		(0.075)	(0.071)	
CCI			-0.504***			-4.664***
			(0.122)			(1.130)
openness	0.033***	-0.024***	-0.012*	0.005	-0.006	-0.000
	(0.005)	(0.008)	(0.007)	(0.005)	(0.010)	(0.012)
government	0.308***	0.489***	0.567***	0.371***	0.412***	0.378***
	(0.045)	(0.053)	(0.034)	(0.048)	(0.086)	(0.104)
natural	-0.068**	0.057**	0.069**	-0.069*	0.070	0.060
	(0.034)	(0.028)	(0.028)	(0.037)	(0.050)	(0.052)
primary	-0.058***	-0.034*	-0.071***	-0.140***	-0.094***	-0.054
	(0.022)	(0.019)	(0.017)	(0.021)	(0.032)	(0.038)
secondary	0.004	0.011	-0.032	0.115***	0.066*	0.052
	(0.038)	(0.046)	(0.050)	(0.025)	(0.038)	(0.043)
minWage	-0.016***	-0.010*	-0.017***	-0.012***	-0.001	-0.009
	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.007)
GDP	-1.598***	-4.188***	-3.808***	-2.929***	-5.944***	-6.350***
	(0.335)	(0.458)	(0.475)	(0.333)	(0.610)	(0.770)
informal		-0.040***	-0.044***		-0.055***	-0.035*
		(0.013)	(0.009)		(0.018)	(0.021)
Constant	63.513***	82.435***	78.578***	72.371***	110.890***	98.606***
	(2.558)	(4.638)	(3.804)	(5.572)	(8.127)	(6.685)
Basmann chi2				5.481	0.599	0.000
(p-value)				(-0.0192)	(0.4387)	(0.9955)
Sargan (score) chi2				5.532	0.625	0.000
(p-value)				(0.0187)	(0.4289)	(0.9954)
Durbin (score) chi2				1.677	26.546	24.531
(p-value)				(0.1952)	(0.0000)	(0.0000)
Wu-Hausman F test				1.648	28.401	26.2742
(p-value)				(0.1997)	(0.0000)	(0.0000)
Cragg-Donald Statistic				14.02	18.407	15.5548
Observations	486	249	215	486	249	215
R-squared				0.407	0.294	0.207

Robust standard errors in parenthesis for GLLAMM models.
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable: Gini index

Note that corruption's coefficient in column 4 shows no statistical significance when the informality variable is not added as a control. However, the IV model in column 4 fails the Basmann and Sargan tests, indicating that our model may not be correctly specified. Because models in columns 5 and 6 have no trouble passing all the tests, we conclude that the inclusion of the informal sector control variable is necessary. We discard the results of column 4 because it also does not pass the Durbin and Wu-Hausman tests. This indicates that informal markets must be accounted for to fully understand the effect of corruption on inequality. As with the GLLAMM model, when the CCI is used as the measure of corruption, the equalization effect of corruption is maintained and is stronger than when the BCI is used (see column 6).

With respect to the controls, we observe that in Latin America inequality is related to (a) greater government expenditures; (b) lower primary education, minimum wage, and economic development, and (c) smaller informal markets. The coefficient of economic openness is only significant in GLLAMMs specifications and with ambiguous signs. This is also the case for the coefficient of natural resources.

All the results above provide us with evidence that perceived corruption has an equalizing effect on income distribution, corroborating Dobson & Ramlogan-Dobson (2012); however, as explained in section 3, perceived corruption measures are not always correlated with experienced corruption measures. In a majority of cases, perception-based measures mostly reflect experts' opinions on what the actual situation may be.

Our paper is the first to overcome this measurement issue by using experienced-based measures to test the relationship between inequality and corruption. An additional methodological advantage is that we do not simply assume corruption is monolithic, and instead consider its effects on the general public (GCB) and firms (ES) to be distinct.

Table 3 provides evidence of the relationship between the general public's experience of corruption and inequality. It uses the GCB index to measure corruption. The first two columns have the Net Gini Index as dependent variables. As a robustness check, we also test the models with

Table 3: General public's experienced corruption and income distribution

	Dependent Variable			
	(1)Gini	(2)Gini	(3)Poor	(4)Rich
GCB	-0.039**	-0.019	0.021***	-0.078***
	(0.017)	(0.016)	(0.005)	(0.027)
openness	0.013**	-0.036***	0.003**	-0.058***
	(0.007)	(0.007)	(0.001)	(0.008)
government	0.256***	0.365***	-0.135***	0.508***
	(0.083)	(0.052)	(0.010)	(0.041)
natural	0.072***	0.056***	-0.073***	0.117***
	(0.027)	(0.020)	(0.003)	(0.037)
primary	-0.033	-0.147***	-0.016***	-0.106***
	(0.027)	(0.014)	(0.003)	(0.020)
secondary	-0.025	-0.062	0.028***	0.042
	(0.039)	(0.040)	(0.003)	(0.036)
minWage	-0.010***	-0.004	0.001	-0.014***
	(0.003)	(0.003)	(0.001)	(0.004)
GDP	-3.676***	-4.151***	0.881***	-3.933***
	(0.380)	(0.398)	(0.071)	(0.515)
informal		-0.111***	0.010***	-0.108***
		(0.008)	(0.002)	(0.009)
Constant	76.888***	88.310***	-2.562***	77.192***
	(3.669)	(3.401)	(0.825)	(5.086)
Observations	111	106	81	81

Robust standard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

two additional dependent variables: income share held by the poorest 20% in column 3, and the income share held by the richest 10% in column 4. We expect that increased public participation in corruption increases the share of income held by the poorest, while decreasing the share held by the richest, as though it were redistributive policy.

The results for public experience-based corruption are similar to the ones reported for perception-based measures of corruption. Column 1 shows that when regular individuals experience more corruption income inequality tends to be lower. A one percentage point increase in the GCB is related

to a 0.039 unit decrease in the net income Gini index. However, when controlling for informality (see column 2), the GCB losses its significance. The redistributive effect that public corruption has is capturing the effect of informality (see column 1). This is consistent with the findings in Dobson & Ramlogan-Dobson (2012). The equalizing effect of public corruption is further confirmed in columns 4 and 5. Higher public corruption is related to a higher share of income held by the poor (see column 3), and to a lower share held by the rich (see column 4). Even when controlling for informal markets, a one percentage point increase in the GCB is related to an increase of 0.021 percentage points in the income share held by the poorest 20%, and a decrease of 0.070 percentage points in the income share held by the richest 10%. Clearly, experience-based corruption in the public at large has the effect of leveling the distribution of income.

Our empirical result provides evidence that is consistent with the burgeoning literature that identifies how corruption can act as a substitute for economic redistribution policies, if the state strategically decides to tolerate law breaking to provide resources to the poor (Holland, 2015, 2016). According to this literature, redistribution happens because corruption allows the general public to operate in informal labor markets that often have lower education and productivity requirements (Dobson & Ramlogan-Dobson, 2010, 2012). Additionally, because poorer individuals can acquire housing in violation of property laws (Holland, 2015). This is consistent with general equilibrium models which have shown that higher corruption can produce decreases in wage inequality (Mandal & Marjit, 2010), larger support for redistribution policies (Alesina & Angeletos, 2005), and diminished poverty (Perera & Lee, 2013).

In the case of Latin America, it has been well-established that corrupt electoral networks have systematically benefited the poor (Calvo & Murillo, 2004; Stokes, 2005), and that officials using bribes to avoid foreign exchange controls have also had positive distributional effects during periods of strong protectionism (Franko, 2007). In the case of Brazil, the work of Ulyssea (2010) has shown that the enforcement of labor market regulations reduces the size of the informal sector, significantly increases unemployment, and produces substantial welfare losses. Holland, in examining

Table 4: Firms' experienced corruption and income distribution

	Dependent Variable			
	(1)Gini	(2)Gini	(3)Poor	(4)Rich
ES	0.049***	0.109***	-0.012***	0.116***
	(0.008)	(0.013)	(0.005)	(0.012)
openness	0.024***	0.000	0.003***	-0.002
	(0.002)	(0.003)	(0.001)	(0.005)
government	0.381***	0.369***	-0.110***	0.482***
	(0.021)	(0.034)	(0.012)	(0.041)
natural	0.227***	0.086***	-0.054***	0.067**
	(0.014)	(0.017)	(0.005)	(0.026)
primary	-0.003	-0.067***	-0.012***	0.041***
	(0.007)	(0.011)	(0.003)	(0.016)
secondary	0.014	-0.115***	-0.005	-0.138***
	(0.015)	(0.020)	(0.005)	(0.028)
minWage	-0.017***	-0.015***	0.003***	-0.018***
	(0.001)	(0.002)	(0.001)	(0.003)
GDP	-2.374***	-2.252***	1.014***	-4.145***
	(0.105)	(0.271)	(0.077)	(0.408)
informal		-0.067***	0.011***	-0.106***
		(0.007)	(0.002)	(0.011)
Constant	60.509***	68.067***	-3.701***	74.592***
	(0.863)	(2.212)	(0.810)	(3.814)
Observations	89	84	64	64

Robust standard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Peru, took an advanced approach to calculate that the tolerance for corruption in street vending in Lima provided a 10 times larger annual income subsidy than the largest social programs in the city (Holland, 2015).

Table 4 provides evidence of the relationship between firms' experience with corruption and inequality. Even with the same control variables, dependent variables, and econometric technique, the results are in sharp contrast with the ones presented before. The results for experience-based corruption in firms are completely different from those of the general public.

In both columns 1 and 2, experience-based corruption for firms has a positive and highly significant coefficient. This means that when acts of corruption are conducted by firms, the previously negative relationship between inequality and corruption disappears. When firms are corrupt, higher corruption leads to higher income inequality. A one percentage point increase in the ES is associated with an increase of between 0.049 and 0.109 points in the net income Gini index. Furthermore, here the informal sector does not directly influence the relationship between corruption and inequality. This result is further confirmed by columns 3 and 4. The negative coefficient in column 3 shows that experience-based corruption in firms is associated with a lower share of income held by the poor. Also, column 4 shows that higher levels of corruption in firms is associated with a higher share of income held by the top 10%. A one percentage point increase in the ES is related to a decrease of 0.012 percentage points in the share of income held by the poorest 20%, and to an increase of 0.116 percentage points in the share of income held by the richest 10%. Altogether, these results confirm that actual corruption in firms increases economic inequality. This is a result that previous studies (those affirming that corruption was associated with lower inequality in Latin America) were incapable of finding because they used perception-based measures and never identified different types of experienced-based corruption.

Our results of firm-level corruption corroborate the arguments of Acemoglu et al. (2002) and Engerman & Sokoloff (2005) that trace large levels of income inequality in Latin America to a corrupt environment that has given capital owners the capacity to develop rules that favor them. In other words, our results also speak to research showing that corruption creates a form of misallocation that favors well-connected firms (Fisman, 2001), and capital owners (Ziobrowski et al., 2004), to the detriment of society. Also, we corroborate the literature that identifies a link between the existence of favored interest groups and reduced redistributive growth (Dincer, 2012), and biased policymaking (Mitchell & Munger, 1991; Carpenter, 2002; Dal Bó, 2006; Gilens, 2012). Accordingly, we also see that many micro-level studies find that politically connected firms obtain prerogatives that the general public lack, and this creates an unfair playing field that worsens

income inequality. In Pakistan, for example, such firms borrow 45 percent more and have 50 percent higher default rates than their peers (Khwaja & Mian, 2005). In areas of Brazil with low institutional quality, higher levels of corruption increase business activity, and at the same time reduce business competition (Bologna & Ross, 2015).

In Table 5, we use FE estimators to further check the robustness of our results. All our results consistently show that actual corruption in firms worsens inequality, while actual corruption among individuals reduces it. First, models measuring actual corruption in society (GCB) show a negative (decreasing) and significant impact on inequality (see columns 1 and 2). A one percentage point increase in the GCB is related to a decrease of about 0.04 units in the net income Gini index. Second, models measuring actual corruption in firms (ES) show a positive (increasing) and significant impact on inequality (see columns 3 and 4). A one percentage point increase in the ES is related to an increase of about 0.1 units in the net income Gini index. Again, this shows that actual corruption in firms widens the income gap, while actual corruption in the public at large narrows it.

Controls in Tables 3 and 4 show that, in Latin America, income inequality is associated with (a) higher government expenditures and higher dependency on natural resources; (b) lower minimum wages, primary education, and economic development; and (c) smaller informal sectors. Economic openness shows significant but mixed results, and secondary education is significant only in column 2 of Table 4. The enhancing effect of government expenditures and the diminishing effects of primary education, minimum wages, economic development, and informal sectors on income inequality were robust throughout all corruption measures (see Tables 2, 3 and 4).

As a whole, the different results we found for corrupt firms and corrupt individuals provide a deeper, more nuanced understanding of the role that informal markets play in shaping the relationship between inequality and corruption. When informality is extensive, as in Latin America, crackdowns on corruption reduce the illicit activities and privileges of firms (Dreher et al., 2009), but they also reduce economic opportunities for the poor and vulnerable (Dobson & Ramlogan-

Table 5: Experienced corruption, fixed effects estimation

	(1)FE	(2)FE	(3)FE	(4)FE
GCB	-0.041*	-0.038*		
	(0.023)	(0.021)		
ES			0.109**	0.103**
			(0.042)	(0.046)
openness	-0.052	-0.086**	-0.013	-0.021
	(0.034)	(0.034)	(0.013)	(0.015)
government	0.382**	0.548**	0.161	0.232
	(0.176)	(0.221)	(0.194)	(0.217)
natural	0.157*	0.147	0.204***	0.173***
	(0.081)	(0.089)	(0.055)	(0.058)
primary	-0.012	0.007	-0.005	-0.004
	(0.129)	(0.123)	(0.132)	(0.136)
secondary	-0.002	-0.016	-0.000	-0.013
	(0.066)	(0.054)	(0.077)	(0.081)
minWage	-0.009**	-0.012***	-0.010	-0.010
	(0.004)	(0.004)	(0.007)	(0.007)
GDP	-4.389***	-4.230***	-3.691***	-3.528***
	(0.722)	(0.568)	(0.578)	(0.692)
informal		-0.086**		-0.047
		(0.033)		(0.035)
Constant	83.191***	85.135***	75.518***	76.157***
	(5.556)	(4.852)	(4.670)	(4.585)
Observations	111	106	89	84
R-squared	0.794	0.819	0.721	0.731
Number of id	17	16	18	17

Robust standard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1
Dependent variable: Gini index

Dobson, 2012). The results of our research have expanded upon and underscored similar findings in the literature[14].

Conclusion

The link between corruption and inequality has been poorly understood because past studies have been seriously flawed in several ways. Firstly, they have assumed that the mere perception of corruption was sufficiently related to actual corruption, and that the effects of corruption would be the same regardless of who participated in it. Secondly, past literature has based its findings solely on the analysis of perception-based measures of corruption that are not suitable for panel analysis (Treisman, 2007). This means that much research is still required to understand the distributional effects of corruption, particularly in Latin America, where a counterintuitive, negative effect of corruption on inequality has been empirically proven (Dobson & Ramlogan-Dobson, 2010; Andres & Ramlogan-Dobson, 2011; Dobson & Ramlogan-Dobson, 2012).

Our paper contributes a deeper and more nuanced understanding of the distributional effects of corruption. We achieved this by (a) testing the relationship between corruption and inequality using a Bayesian corruption estimate that is suitable for panel analysis, and (b) using experienced-based corruption measures that distinguish between the corruption that affects firms and the general public.

With three different specifications (mixed-effect estimates, fixed-effect estimates and instrumental variable models), we provide the most holistic test conducted to date. This enables us to show that, in Latin America, perceived corruption has a negative relationship with inequality, as does actual corruption, but only when the general public is participating in it. When firms are corrupt, corruption has a more intuitive, positive relationship with inequality. To illustrate, recall that a one percentage point increase in the ES was associated with an increase of between 0.049

[14]Our research could also eco the findings in Dreher & Schneider (2010), according to which the effect of corruption crackdowns may be heterogeneous, depending on country income levels.

and 0.109 points of net income in the Gini index (greater corruption in firms means higher income inequality).

Furthermore, we provide evidence that corruption affecting the public tends to increase the income share of the bottom 20%, while corruption affecting firms tends to increase the income of the top 10%. Recall that a one percentage point increase in the ES is related to an increase of 0.116 percentage points in the income share held by the richest 10%, while a one percentage point increase in the GCB is related to an increase of 0.021 percentage points in the income share held by the poorest 20%. We attribute these results to the diverse ways in which economic and legal privileges are distributed when corruption affects individuals, as opposed to capital owners.

Our empirical results provide evidence that is consistent with an important burgeoning literature that identifies how corruption can act as a substitute for economic redistribution performed by the government (Holland, 2015, 2016). We also corroborate Acemoglu et al. (2002) and Engerman & Sokoloff (2005) in finding that a critical source of extreme economic inequality is corruption among economic elites who can shape the system to privilege themselves further. This is exemplified in our result that the corruption of firms benefits the economic elites, the richest 10%. Since firms tend to be active perpetrators of bribery (Ufere et al., 2012)[15], the owners of capital seem to be exploiting weak and permissive institutions in their benefit.

Further development of this research area is vital, because it will inform policy makers that not all kinds corruption have the same redistributive effects. Anti-corruption policies targeting corrupt capital owners and elites may reduce inequality, however, targeting the general public may increase inequality in economies with large informal markets. Despite the progress we made with this study, more research is needed to identify the heterogeneous effects caused by other different types of corruption not addressed here.

[15]The general public, on the other hand, depends much more on public services where they are more likely to be victims of the corrupt behavior of street bureaucrats. (Justesen & Bjørnskov, 2014).

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