Corruption type and income inequality in Latin America

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ABSTRACT
This paper contributes to understanding an unresolved schism between scholars who have observed that inequality increases as corruption increases and those who have found the opposite. We show that identifying different types of corruption matter in this debate. When corruption takes the form of individual-level bribery, it is related to lower inequality because it allows informal markets to survive. Yet, when corruption takes the form of bribery at the firm-level, it may be related to higher income inequality by promoting the existence of less competitive markets. Using panel-suitable Bayesian estimates of corruption and measures of experienced corruption, we find that corruption at the individual-level is related to an increase in the share of income held by the bottom 20%. Meanwhile, firm-level corruption is related to a higher share of income held by the top 10%. Furthermore, large informal markets enhance the negative relationship between individual-level corruption and inequality while higher favouritism by authorities when assigning public funds enlarges the positive relationship between firm-level corruption and inequality. We provide case studies of Bolivia, Brazil, Colombia, and Mexico to further solidify our empirical findings. Our results indicate a pressing need to develop a more precise picture of how corruption and inequality interact.

1. Introduction

Corruption is an undeniably important area of interest for social scientists. Yet, even though political corruption has long been subject to empirical scrutiny, its relationship with economic inequality remains enigmatic. The common sense view, that income inequality increases as corruption increases, has been borne out by studies that have identified a positive effect of corruption on income inequality (Dincer & Gunalp, 2012; Dong & Torgler, 2013; Gyimah-Brempong & de Munoz, 2006; Li, Xu, & Zou, 2000). However, mounting evidence has shown that increases in corruption, particularly in Latin America, are also associated with reductions in income inequality (Andres & Ramlogan-Dobson, 2011; Chong & Calderon, 2000; Dobson & Ramlogan-Dobson, 2010, 2012).

We build on studies that have identified different forms of corruption. The core idea of this literature is that corruption is not a monolithic activity but rather a set of differentiated actions that may have different causes and consequences. We argue that these mixed findings could be better understood by considering how different types of corruption may affect the allocation of illegal privileges/benefits. Inspired by Rose-

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Ackerman (1999), Svensson (2003), and others (Banerjee, Mullainathan, & Hanna, 2012; Heidenheimer, 2002; Johnston, 2005; Nyblade & Reed, 2008; Olken & Barron, 2009; Ruhl, 2011; Shleifer & Vishny, 1993), this perspective suggests that what matters to distribution is not the level of corruption, but rather the type of corruption.

Our theoretical framework boils down to a couple propositions: When corruption takes the form of bribery at the individual-level, it may reduce inequality by spurring an informal market in which less well-off individuals can more readily participate and more easily become economically productive (Andres & Ramlogan-Dobson, 2011). This is the case because corruption reduces the costs of participation in informal markets by providing a second-best alternative that avoids regulatory barriers to entry. Yet, when corruption takes the form of firm-level bribery, it may increase inequality by reducing competition and enabling favouritism. The bribing of public officials by firms seeking public contracts, for example, could concentrate wealth in hands of already connected, affluent individuals and firms (Ufere, Perelli, Boland, & Carlsson, 2012).

The hypothesis that different distributional outcomes are conditional on types of corruption may have remained unexamined until now, in part, due to some common empirical assumptions that this paper does not share. First, unlike most studies, we do not rely on measurements of perceived corruption because it is weakly correlated with real acts of corruption (Abramo, 2008; Donchev & Ujhelyi, 2014; Razafindrakoto & Roubaud, 2010). Second, we do not fail to address the fact that most corruption perception series may not be entirely comparable over time, given their abundant methodological changes and inherent behavioural biases (Treisman, 2007). Instead, we use panel-suitable Bayesian estimates of corruption (Standaert, 2015). Finally, we do not use compounded indexes which implicitly assume that corruption is a monolithic illegal behaviour that affects society in general. Instead, we aspire to attempt to measure critical differences among types of corruption (Banerjee et al., 2012; Heidenheimer, 2002; Johnston, 2005; Nyblade & Reed, 2008; Olken & Barron, 2009; Ruhl, 2011; Shleifer & Vishny, 1993), particularly between corruption experienced by firms and by individuals.

Our empirical analysis provides an initial test of the distributive effects of different corruptions. Our database is strongly balanced and included 18 countries from Latin America and spanned the years between 1999 and 2013[2]. Controlling for factors previously identify as determinants of redistribution, we show that individual-level corruption is related to lower inequality and a lower share of income held by the top 10 percent. Yet, firm-level corruption is related to greater inequality and a greater share of income held by the top 10 percent.

We go on to try to explore possible mechanisms to these results on two ways. First, we present a preliminary empirical analysis to show that, as expected, the marginal effect of individual-level corruption on inequality is stronger when informal markets are large. Also, we shows that the marginal effect of corruption at the firm-level is larger when the government tend to be more favourable towards certain firms. The second step is more qualitative. We present cases that exemplify our mechanisms in Bolivia, Brazil, Mexico and Colombia. Our evidence on this score is far from definitive, but it suggests that when firm-level corruption and firm favouritism go hand in hand, as in some industries in Mexico and Colombia, a small set of firms may get larger profits thus possibly pushing income inequality up. Also, when informality and individual-corruption tend to be together, additional sources of income may be created for poorer

[2]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).

layers of society, thus possibly lowering inequality.

The rest of the paper is structured as follows. The second section fleshes out our argument regarding the distributional effects of corruption, the third describes the datasets, the fourth our identification strategy, and the fifth our main results. The sixth section provides an exploration of the possible mechanisms of the previously found results and illustrates with case examples from Bolivia, Brazil, Mexico and Colombia. We conclude in the seventh section.

2. The distributional effects of corruption

Corruption, here defined as 'the misuse of public office for private gain' (Gyimah-Brempong, 2002; Treisman, 2000), has oddly mixed redistributive outcomes. While some studies find that corruption increases income inequality (Dincer & Gunalp, 2012; Dong & Torgler, 2013; Gyimah-Brempong & de Munoz, 2006; Li et al., 2000), others, particularly in Latin America, find the opposite (Andres & Ramlogan-Dobson, 2011; Chong & Calderon, 2000; Dobson & Ramlogan-Dobson, 2010, 2012).

We argue that the inconsistent findings in the literature could be explained by how different types of corruption affect the allocation of illegal privileges/benefits. In particular, we explore how corruption at the individual-level and firm-level may have different effects. In this sense, our work empirically considers the existence of different types of corruption, as qualitative research has long advocated for (Johnston, 2005; Rose-Ackerman & Palifka, 2016). Our appraisal of the literature leads us to two hypotheses:

H1: Income inequality decreases with individual-level corruption.

Corruption could create informal economic opportunities for vulnerable individuals, who would otherwise be unable to afford the cost of operating in complete compliance with the rules of the formal economy (Méon & Sekkat, 2005; Méon & Weill, 2010; Sarte, 2000). Thus, corruption may reduce inequality by granting vulnerable populations access to income sources outside legally regulated markets (Andres & Ramlogan-Dobson, 2011; Dobson & Ramlogan-Dobson, 2012). In other words, corruption could be a second-best substitute to functional markets (Huntington, 1968; Leff, 1964).

Furthermore, corruption may be negatively related to inequality when vote buying is common. This is because corrupt electoral networks may benefit the poor by distributing goods and public services in exchange for votes (Calvo & Murillo, 2004; Holland, 2016; Stokes, 2005; Wong, 2016). Thus, corruption may reduce income inequality by allowing the state to strategically decide to tolerate law breaking that provides resources to the poor. In many ways, this is consistent with the burgeoning literature that identifies how corruption can act as a substitute for economic redistribution policies (Holland, 2015, 2016).

H2: Income inequality increases with firm-level corruption.

Firm-level corruption may be positively related to inequality, particularly where favouritism and monopolies are common. This is because corruption could further entrench an economic environment that disproportionately favours some actors, or where some corrupt entities find it easier to become richer (Glaeser, Scheinkman, & Shleifer, 2003).

Wealth can enable firms to buy influence both legally and illegally (De Ferranti, Perry, Ferreira, & Walton, 2004; Glaeser et al., 2003; Kaufmann, 1997; Kaufmann &

Hellman, 2002), thus creating an 'inequality of influence' (Fried, Lagunes, & Venkataramani, 2010; Ruhl, 2011). Corruption may allow bureaucrats to conspire with capital owners to generate extra-normal rents, or to redistribute income towards the wealthiest corporations (Dong & Torgler, 2013). Indeed, some evidence shows that firm-level corruption may concentrate public funds in the hands of business elites (Wong, 2016).

As a result, some scholars have argued that large levels of income inequality can be traced to a corrupt environment that gives capital owners the capacity to develop rules that favour them (Acemoglu, Johnson, & Robinson, 2002; Engerman & Sokoloff, 2005). This creates all sources of benefits, from shields from high bribery demands (Rose-Ackerman, 1999; Svensson, 2003), to more lenient inspections (Nielsen, 2006), fewer hassles from border officials (Fadahunsi & Rosa, 2002), and even better treatment from bureaucrats working at the cabinet level (Lagunes, 2009).

In other words, corruption tends to create a form of misallocation that favours well-connected firms (Fisman, 2001), and capital owners (Ziobrowski, Cheng, Boyd, & Ziobrowski, 2004), to the detriment of society. The literature also identifies a link between the existence of favoured interest groups and reduced redistributive growth (Dincer, 2012) and biased policymaking (Carpenter, 2002; Dal Bó, 2006; Gilens, 2012; Mitchell & Munger, 1991). Accordingly, we also see that many micro-level studies find that 'politically connected' firms obtain prerogatives that individuals lack, and this creates an unfair playing field that worsens income inequality (Bologna & Ross, 2015; Khwaja & Mian, 2005).

The theoretical arguments underlying H1 and H2 have not been empirically identified until now because most corruption studies rely on measurements of perceived corruption. This is problematic as perceptions may not necessarily imply victimisation. Actually, perception measures are not equally correlated with all types of experienced corruption (Bohn, 2013; Morris, 2008; Ruhl, 2011; Seligson, 2006; Zéphyr, 2006). Individual-level experiences of corruption seem to be more correlated with perception of corruption than firm-level experiences of corruption. As Figure 1 shows, while the correlation between individual-level corruption and perception of corruption is 0.62, the correlation with firm-level is only 0.48.

[Figure 1 about here.]

3. Data

3.1. Corruption

We measure corruption perception using a new estimate: the Bayesian Corruption Indicator (BCI). The BCI was very recently developed by the Study Hive for Economic Research and Public Policy Analysis (SHERPPA) at Ghent University, with the goal of correcting the problems of other corruption perception measures (Standaert, 2015).

The most important problem with the most commonly used measures of corruption (the Corruption Control Index (CCI) and the Corruption Perception Index (CPI)) is that they have been criticised as unsuitable for longitudinal analyses. Their sources and informants are sometimes different from year to year (Hawken & Munck, 2011; Standaert, 2015; Treisman, 2007), making interpretation problematic unless we assume that the underlying parameters of these two different samples are equivalent[3]. Furthermore, CPI's methodology has changed overtime, creating an omitted variable

[3]See the work of Arndt and Oman (2006) and Knack (2007) for evaluations of inconsistencies.

that could be driving changes in corruption.

The BCI makes three important contributions. First, it employs a state space model that makes use of the persistence of corruption over time to more effectively identify real changes. Second, the Bayesian Gibbs sampling algorithm and the solution to missing data allows the BCI to obtain values without assumptions or manipulations of the original data. Third, due to its flexibility, the Bayesian Gibbs sampling algorithm considers different types of measurement errors (cross-correlated and persistent) in the original data (Standaert, 2015).

The result is an unbiased indicator that is methodologically more solid than the CPI or CCI and allows for comparisons over time. BCI has been rapidly accepted by academics and is becoming a reliable part of many empirical studies[4] (Ferrali, 2017; Ouattara & Standaert, 2017).

In addition to the use of BCI, this paper complements previous literature by using measures of experiences with corruption.

We believe experience-based measures may be particularly valuable to understand policy outcomes as they do not capture what people 'think', but rather whether individuals have been, indeed, illegally requested for a gift, money, or other inducement to get access to a public good or service. Indeed, this measure is far from perfect too. Individuals may lie about their encounters with corruption because they may not want to be indirectly incriminated. Overall, there is no perfect measure of corruption, which is why methods like ours that use different measures to test a single hypothesis are becoming a best practice among academics. For many years, academics had ignored these measures due to the limited number of time periods available for study. Fortunately, as of now, these measures have accumulated enough observations.

We measure individual-level corruption with an experience-based indicator obtained from the Global Corruption Barometer (GCB) (Transparency International, 2013). The GCB is the only cross-national longitudinal public opinion survey measuring direct experiences with corruption by individuals ('In the past 12 months, have you or anyone living in your household paid a bribe in any form?'). It has been conducted 8 times between 2003 and 2013 in 125 countries, and is based on interviews with a sample of the adult population. Notably, it may be the case that corruption experienced by individual firm owners gets captured by this measure, too. However, since the aim of the GCB is to capture information about the entire adult population, firm owners will represent a minority of total respondents. Therefore, the results of using this variable would still capture different phenomena than the firm-level corruption measure.

We also measure firm-level corruption with an experience-based indicator, the Bribery Incidence of the Enterprise Survey (ES) (World Bank, 2017b). The ES was carried out at different times in 134 different countries between 2006 and 2015, but most of the observations are grouped between 2009 and 2011, and a majority of the countries have only one observation. The survey captures the percentage of firms that report experiencing at least one bribe request when dealing with utilities access, permits, licenses, and taxes. The firms surveyed were all formal (registered), representative by size and geography, and did not come from a specific industry.

Note that both corruption measures are positively correlated as Figure 2 ($\rho = 0.55$) shows.

[4]Even if the BCI is a better measure than others previously used, we understand that the measure is far from perfect. What respondents understand as 'corruption' may vary from country to country (Treisman, 2007). Therefore, in the literature and in this paper, measures of 'perceptions of corruption' should not be understood as measures of corruption per se. Instead, they should be understood as measures of opinions about the existence of what individuals believe to be corruption.

[Figure 2 about here.]

3.2. Inequality

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 Socio-Economic Database for Latin America and the Caribbean (SEDLAC) and the Luxembourg Income Study Database (LIS), and secondary sources, like the All The Ginis Dataset of the World Bank. Imputation of missing data allows the SWIID to have the greatest coverage of Gini indices in both time and space (Ferreira, Lustig, & Teles, 2015). SWIID also maximises comparability and is better suited to longitudinal panel analysis (Solt, 2016).

Specifically, we use the net Gini index which is based on inequalities of household disposable income. In other words, gross income minus direct taxes, or income inequality post-taxes and post-transfers. We choose the Gini of disposable income over the Gini of market income because the latter would exclude possible corrupt interactions between the government and citizens via money transfers and tax payments.

As mentioned in Desbordes and Koop (2016), criticisms of the older versions of the SWIID have been addressed by this newest version[5] (Ferreira et al., 2015; Jenkins, 2015; Solt, 2015). Furthermore, as Desbordes and Koop (2016) stated, the appropriate practice when using indicators of political-economic development is to take standard errors into account through the use of multiple imputation. The SWIID already provides imputations, in fact, Desbordes and Koop (2016) directly use the net Gini index, which is the same variable that we use, in their tests.

In robustness tests, the share of income held by the poorest 20 percent of the population (Poor), and the share of income held by the top 10 percent (Rich) were both used as dependent variables (World Bank, 2017c).

In robustness tests, the share of income held by the poorest 20 percent of the population (*Poor*), and the share of income held by the top 10 percent (*Rich*) were both used as dependent variables (World Bank, 2017c).

3.3. Other variables

The size of the informal economy (as percentage of GDP), *informal*, was estimated using data from Hassan and Schneider (2016). Throughout this paper, the terms informal economy, informal markets, and informality will be used interchangeably when referring to the data in Hassan and Schneider (2016). citedobson2012corruption had already used this dataset, but for a much more limited time frame. Other studies have measured informality using data from the SEDLAC, however, we did not use data from this source because it has comparably too few observations.

As a proxy to measure vote buying, we use panel data from the Varieties of Democracy (V-Dem) (Coppedge et al., 2016) available at The Quality of Governance Standard Dataset 2017 (Teorell et al., 2017). *VoteBuying* measures whether experts believe that there was evidence of vote and/or turnout buying in national elections. V-Dem uses

[5]Earlier versions of the SWIID classified the source data according to 19 categories defined by welfare definitions and the equivalence scale used in their calculation; however, some were not coherent, and included observations for which the welfare definition was unknown Solt (2016). Such observations were excluded in newer versions.

a specifically designed measurement model that considers disagreement and measurement error (Teorell et al., 2017). The variable is multiplied by (-1) so that a higher value of *voteBuying* represents a higher level of vote buying.

To account for an environment in which corruption is paired with an unwillingness to provide a level playing field for firms, (the latter is when a government favours well-connected firms and individuals when deciding upon policies and contracts and/or has no intention of providing effective anti-monopoly sanctions), we use data from the World Economic Forum[6] (Schwab & Sala-i Martin, 2015). Specifically, we use two variables from the Global Competitiveness Report, which remains the most comprehensive assessment of national competitiveness worldwide (Teorell et al., 2017). Both variables were obtained through the Executive Opinion Survey, a survey of business executives in each of the countries for which data are available.

The first variable, *favouritism*, assesses the extent to which governmental officials show favouritism towards certain firms when making choices. Specifically, executives are asked 'In your country, to what extent do government officials show favouritism to well-connected firms and individuals when deciding upon policies and contracts?'. Executives then choose an option between 1, they show favouritism to a great extent, and 7, they do not show favouritism at all. The variable is multiplied by (-1) so that a higher value indicates that officials tend to show favouritism.

A second variable, *monopoly*, assesses how effectively anti-monopoly policies promote competition. Specifically, executives are asked 'In your country, how effective are anti-monopoly policies at ensuring fair competition?'. Executives then choose an option between 1, not effective at all, and 7, extremely effective. Again, the variable is multiplied by (-1) so that a higher value means anti-monopoly policies do not promote competition.

Our models employ several control variables that have been regularly used in the literature on corruption and inequality (Andres & Ramlogan-Dobson, 2011; Dobson & Ramlogan-Dobson, 2012; Gupta, Davoodi, & Alonso-Terme, 2002; Gyimah-Brempong, 2002; Pedauga, Pedauga, & Delgado-Márquez, 2017).

Following Dobson and Ramlogan-Dobson (2012), we include measures of the population over 15 years old with either *primary* or *secondary* education. This data was obtained from the widely used Barro-Lee dataset (World Bank, 2017a). We also control for the minimum wage, *minWage*, using an index constructed by CEPALSTAT, as used in Cornia (2013). Finally, we took other controls from the World Bank's World Development Indicators (World Bank, 2017c). *Openness* is the sum of exports and imports in relation to GDP. *GDP* is the natural logarithm of GDP per capita. *Natural* is the percentage of GDP that comes from natural resources. *Government* is government consumption as a percentage of GDP. Table 1 shows descriptive statistics. Our database includes 18 countries from Latin America (1999 - 2013)[7].

[Table 1 about here.]

4. Model Specifications

We test the relationship between inequality and corruption using two econometric specifications: Generalised Linear Latent and Mixed Model (GLLAMM) and Instrumental Variables Model (IV). We consider a linear relationship between inequality and

[6] Data was downloaded from The Quality of Governance Standard Dataset 2017 (Teorell et al., 2017).

[7] All models were ran with and without Venezuela as a robustness test.

corruption, hence our model would be:

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

where i represents the country, t the year, I the degree of income inequality (a higher value represents greater inequality), C a corruption measure (a higher value represents greater corruption), X a vector of covariates and μ_i the deviation of country i's true exposure from the mean exposure for covariate X_i.

When assessing the relationship between income inequality and corruption, measurement error is a concern. However, we feel confident about our variables. The algorithm used to generate the BCI is better able to distinguish between actual changes in the level of corruption and measurement errors because it makes use of the persistence of corruption over time and considers different types of measurement errors in the original data . Yet, we still do not take the matter lightly. As Rabe-Hesketh, Pickles, and Skrondal (2003) has explained, considering measurement errors is crucial in order to eliminate biases from the estimates of the regression parameters, and to facilitate the prediction of the true covariate, or exposure for an individual country.

The GLLAMM is particularly well suited to our purposes because it corrects for changes in the variance of measurement errors over time (see Rabe-Hesketh et al. (2003)). If corruption, our main explanatory variable, is still measured with error, conventional linear models can yield biased estimates of parameters. Hence, the general structure of the GLLAMM model is:

$$i_{i,t} = I_{i,t} + \eta_{i,t}$$

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

$$i_{i,t} = \beta_0 + \beta_1 C_{i,t} + \beta_2 X_{i,t} + \mu_i + \eta_{i,t}$$

where 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.

Several studies point to problems of endogeneity in trying to estimate the effect of perceived corruption on inequality (Apergis, Dincer, & Payne, 2010; Dobson & Ramlogan-Dobson, 2012; Gupta et al., 2002; Gyimah-Brempong, 2002; Gyimah-Brempong & de Munoz, 2006; Li et al., 2000). Therefore, in addition to GLLAMM models, we used an IV model to estimate the relationship between perceived corruption and inequality[8]. The general structure of the 2SLS model is:

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

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

[8]IV specifications cannot be used for experience-based corruption measures. The development of adequate instruments for corruption measures based on experiences will be inspected in future investigations.

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 with an error ζ.

Much published research has used democracy (Dobson & Ramlogan-Dobson, 2012; Gupta et al., 2002), and settler mortality (Dobson & Ramlogan-Dobson, 2012; Gyimah-Brempong, 2002; Gyimah-Brempong & de Munoz, 2006), as instruments to capture corruption perceptions.

We understand these instruments have been criticised, as all instruments generally are. Yet, we decided to use them only in one of the five different empirical specifications presented in this paper as a robustness check. Much published research has been done using them as instruments for corruption perceptions.

Our first instrument was measured using a dichotomous index of democracy, as created by Acemoglu, Naidu, Restrepo, and Robinson (in press)[9]. The reason for this 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 measure we used 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, Gandhi, and Vreeland (2010) or in Boix, Miller, and Rosato (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 seen in the case of Mexico, having a declared dictator does not necessarily mean that the index constructed in Acemoglu et al. (in press) considers a country undemocratic.

Our second instrument, the natural logarithm of the mortality rate faced by European settlers, was extracted from the dataset in Acemoglu, Johnson, and Robinson (2001). Colonisation strategies were influenced by the viability of the settlements such that a higher mortality rate for the settlers negatively affected the probability of creating 'Neo-Europes', and positively affected the probability of creating extractive colonial institutions. Extractive colonial institutions tend to be more corrupt.

We test whether our model was correctly specified following Sargan (1958) and Basmann (1960) chi2. As expected, we rejected both tests (see columns 4 and 5, Table 2). Also, we use Durbin (1954) chi2 and Wu-Hausman (Hausman, 1978; Wu, 1974) F tests to check if an IV estimator is needed. The IV technique is worth using only if both tests are significant. As expected, we rejected both (see columns 4 and 5, Table 2). Finally, we tested the weakness of our instruments using the Cragg and Donald (1993) minimum eigenvalue statistic. Stock and Yogo (2005) defined instruments as weak if a Wald test at the 5 percent level has a rejection rate of no more than 25 percent. Our Cragg and Donald statistic exceeds 11.59, which is the critical value at the 15 percent rejection rate. Given the outcomes of these tests, we are confident in our results.

[9] Research shows that democracy has a mitigating 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, Agudelo, & Hassan, 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.

5. Main Empirical Results

Table 2 shows a negative relationship between perceived corruption and income inequality in Latin America. This confirms H1 for perception-base measures.

Our favourite specification (model 2), shows that a one unit increase in *BCI* is associated with a decrease of 0.045 units in the Gini. When using *CCI*, this effect is even more pronounced, indicating that corruption measures not suitable for panel analysis may overestimate the effect. These results hold with the IV technique (columns 4 and 5), where a one unit increase in the *BCI* is related to a 0.31 decrease in the net income Gini (column 4)[10]. Moreover, corruption perceptions seem to be associated with a higher income share held by the poorest (column 6), and a lower income share held by the rich (column 7).

[Table 2 about here.]

Table 3 shows a negative relationship between individual-level corruption and income inequality. It confirms H1 for experienced-based measures.

In our favourite specification (column 2), a one percentage point increase in the *GCB* is related to a 0.028 unit decrease in the Gini. Note that all models are estimated using the GLLAMM method, because there are not more appropriate instruments for experienced corruption variables. Moreover, when controlling for informality (see column 2), the *GCB* keeps its significance[11].

[Table 3 about here.]

The negative relationship between individual-level corruption and inequality is further substantiated in columns 3 and 4 in Table 3. Higher individual-level corruption is related to a higher share of income held by the poor and to a lower share held by the rich. Even when controlling for informal markets, a one percentage point increase in the *GCB* is related to an increase of 0.015 percentage points in the income share held by the poorest 20 percent, and to a decrease of 0.076 percentage points in the income share held by the richest 10 percent.

Table 4 shows a positive relationship between firm-level corruption and income inequality. It confirms H2 for experienced-based measures.

In our preferred model (column 2), a one percentage point increase in the *ES* is associated with an increase of between 0.043 and 0.083 points in Gini. Note that, in this case and as expected, the informal sector does not directly influence the relationship between corruption and inequality. A one percentage point increase in the *ES* is related to a decrease of 0.022 percentage points in the share of income held by the poorest 20 percent, and to an increase of 0.11 percentage points in the share of income held by the richest 10 percent[12].

[Table 4 about here.]

The results presented in this section are consistent with our theory of how types of corruption may be influencing redistribution, but they do not show how this relationship is operationalized. In other words, they do not address how types of corruption

[10] This relationship is almost seven times stronger than the one estimated using the GLLAMM model, indicating that not accounting for the endogeneity problem could underestimate the actual relation.

[11] As a robustness test, we also specified our model as a panel with observation-level Fixed Effects by country. Results do not change and are available at the appendix

[12] As a robustness test, we also specified our model as a panel with observation-level Fixed Effects by country. Results do not change and are available at the appendix

translate into redistributive outcomes. In the reminder of the article, we attempt to, very preliminary, address these questions.

6. Exploration of mechanisms

In accordance to our theoretical framework, Table 5 shows the results of a first attempt to explore some possible mechanisms behind the different distributive outcomes of different types of corruption.

We tested whether the marginal effect of individual-level corruption on inequality is stronger where informality and vote buying are stronger, and whether marginal effect of firm-level corruption is stronger where monopolies or favouritism are stronger.

We present GLLAMM models, results for panel regressions with Fixed Effects (FE) per observation, and Bayesian model-averaging (BMA) estimators as developed by (Magnus, Powell, & Prüfer, 2010). We use BMA because, unlike standard pretest estimators that are based on some preliminary diagnostic tests, this model provides a coherent way of making inference on the regression parameters of interest by taking into account the uncertainty due to both the estimation and the model selection steps. We distinguish between focus regressors that are always included in the model (corruption and controls), and auxiliary regressors (possible mechanisms) of which we are less certain. Note that, on BMA models, we report the posterior inclusion probabilities (pip), instead of standard errors for the variables related to possible mechanisms. A regressor is considered to be robustly correlated with the outcome if the pip is 0.5 or larger (Masanjala & Papageorgiou, 2008; Raftery, 1995).

[Table 5 about here.]

[Figure 3 about here.]

To facilitate interpretations, we present Figure 3 with marginal effects for our preferred models (columns 1 and 4).

Using the results of the first column of Table 5, the first graph of Figure 3 shows that the marginal effect of individual-level corruption on inequality is more negative when informality is larger. This could be very preliminary evidence that corruption may create more income redistribution when it comes along with informal economic opportunities. As the theory would predict (Andres & Ramlogan-Dobson, 2011; Dobson & Ramlogan-Dobson, 2012), when corruption goes hand in hand with informality, vulnerable individuals who would otherwise be unable to afford the cost of operating in complete compliance with the rules of the formal economy, are able to be part of informal labour markets (Méon & Sekkat, 2005; Méon & Weill, 2010; Sarte, 2000). Thus, creating an income for poor and low educated individuals.

Interestingly, the marginal effect is not significantly different when vote buying is common. This is preliminary evidence showing that corrupt electoral networks may be less important to understand inequality than informality (Wong, 2016).

The exploratory nature of the exercise presented in Figure 3 is supported by the FE and BMA models (columns 2 and 3). In particular, the results of the BMA confirm that the interaction between individual-level corruption and informality is a better predictor than the interaction between individual-level corruption and vote buying.

A good example of this type of relationship between individual-level corruption and informality is Bolivia. There is some evidence that Bolivia's informal workers have benefited from bribing authorities because bribes make their income flows more predictable (Hummel, 2017). Bribes allow them to operate constantly in the informal market without fear of income disruption. This is critical because, most informal workers in Bolivia, like in most areas of Latin America, lack the education needed to successfully integrate into the more productive and predictable formal economy (Dobson & Ramlogan-Dobson, 2012). Without recourse to bribes, many vulnerable individuals could not earn a living in the formal economy. This has implications for overall levels of income inequality.

In some ways, this phenomenon relates to the concept of 'forbearance', or intentional and revocable government leniency toward violations of the law, which works as an informal welfare policy when directed at the poor (Holland, 2016). Accordingly, authorities may often permit informal activities depending on the monetary or political benefits. For instance, in poorer districts forbearance may be a way to earn political support by somewhat alleviating the plight of the poor.

Similarly, in Brazil, it has been documented that a stricter application of the law left unprepared workers without a stable income (Itikawa, 2006). According to Itikawa (2006), authorities in São Paulo tend to use licenses as political commodities that they 'negotiate' with informal workers. Only their 'protégés' can remain on the streets without a license. In the same vein,Ulyssea (2010) shows that policies that directly increase the cost of operating in informal markets have negative effects on the welfare of the poorest in Brazil.

Using the results of the fourth column of Table 5, the second graph of Figure 3 shows that the marginal effect of firm-level corruption on income inequality is more positive in presence of higher favouritism of governmental authorities. This preliminary evidence shows that corruption may derive into higher income inequality when it comes along with authorities favouring already well-connect firms. Well-established businessmen and connoisseurs of bribery practices are better able to obtain contract resources provided by corrupt state officials, who already have their 'favourites' when allocating resources (Ufere et al., 2012). Note that the effect of monopoly is less consistent.

FE and BMA models further support the findings (columns 5 and 6). The interaction between firm-level corruption and preference is a better predictor than the interaction between firm-level corruption and monopoly.

A good example of the relationship between firm-level corruption and favouritism is Mexico, where favoured companies seem to be common in some industries (Esquivel, 2015). Consider the case of the Mexican mining industry, where concessions for the exploitation rights are generally associated with some kind of bribery, and are granted to traditionally favoured entrepreneurs despite the possible land dispossession and pollution impacting rural communities (Department for International Trade, 2018).

This practice is likely to increase inequality by worsening the situation of the least well-off. It has been documented that officials have allowed projects, despite the negative effect they could have on the livelihood of often extremely impoverished people (Department for International Trade, 2018). These projects are often developed in rural areas where indigenous and agricultural communities are established, further decreasing their opportunities for a better life and increasing inequality (Department for International Trade, 2018). Furthermore, inequality increases, not only because of privileged concessions, but also because of fiscal privileges that are granted to favoured mining entrepreneurs (Esquivel, 2015).

Similarly, in Colombia favouritism during the procurement process allows for the diversion of resources to corrupt firms, negatively affecting those that were supposed to have benefited from government investment (Schwab, 2018). In 2014, a Colombian senator was prosecuted for diverting more than 500 million dollars, originally earmarked for productive investment in Bogota, to favoured companies (Anselma, 2014). In another example, a former Minister of Agriculture diverted resources from agricultural subsidies targeting poor peasants to wealthy people, including wealthy landowners, politically powerful families, and even a beauty queen (Medendorp, 2014).

There are many other well documented cases of corruption associated with favouritism in the public procurement process (see GAN Business Anti-Corruption (2018)). All these cases have two common characteristics (Esquivel, 2015). First, rich people are using their political influence, corrupt networks, and a weak judicial system to further enrich themselves. Second, the livelihoods of less well-off individuals are negatively affected by the diversion of funds. In these cases, corruption allows entrepreneurs to take advantage of weakly guarded procurement processes to appropriate resources originally intended to benefit the poor.

In sum, there is some evidence that seems to show that H1 and H2 cannot be rejected, and that the most empirically supported mechanism behind these relationships is the interaction between individual-level corruption and informality, and between firm-level corruption and favouritism. Further theoretical and empirical work is necessary to clarify the role of informality and favouritism in the relationship between corruption and inequality. Our paper, is just one step into that direction.

7. Conclusion

Studies of the relationship between corruption and inequality have left scholars with pretty mixed results. This paper posits that comprehending these results may require a more nuanced understanding of corruption. One that allows us to explore how different types of corruption may affect the allocation of illegal privileges/benefits.

Using experienced-based corruption measures that distinguish between corruption that affects firms and individuals, our analysis suggest that individual-level corruption has a negative relationship with inequality, and firm-level corruption has a positive relationship.

Some of our results show that the negative relationship between inequality and individual-level corruption may be explained by informal markets. Corruption enables poor individuals to gain income by operating in informal markets. Without informality, many poor individuals would be unable to make a living because they lack the skills and education needed to participate in formal markets, and this is likely to exacerbate already dire economic inequalities. We presented examples from Bolivia and Brazil that show this relationship.

We also found that firm-level corruption is related with greater inequality when corruption allows for the existence of favouritism on the part of the authorities. Examples from Colombia and Mexico showed how, particularly in cases of government procurement, favoured firms may capture benefits that could otherwise be used to benefit the poor.

Most importantly, our paper should be considered a preliminary exploration of the relationship between corruption and inequality. More research is needed to identify the heterogeneous effects caused by other types of corruption not addressed here, and to identify the ways in which corruption may be related with long/short term changes in income inequality. However, this line of research is vital to policy makers who should be informed that all types of corruption may not have the same redistributive outcomes. Anti-corruption policies targeting corrupt firms may reduce inequality; yet, targeting individuals may increase inequality in economies with large informal markets, if no productive alternative is provided to the informal workers.

In addition, there is a need for a better identification of the mechanism that drives these results. An interesting variable could be the level of government in which corruption takes place. Firms may be in contact with higher levels of government while people are in contact with lower levels. Unfortunately, currently our measures of experienced corruption do not allow us to measure this difference. Also, the research would benefit from the development of suitable instruments for the different corruption measures such that IV techniques can be applied. Other techniques such as dynamic panel models would also advance the field.

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List of Tables

Table 1. Summary statistics.

VARIABLES	N (1)	Mean (2)	Sd (3)	Min (4)	Max (5)
BCI	558	52.28	8.39	30.36	68.31
CCI	306	0.31	0.69	-1.57	1.44
GCB	113	16.81	10.04	3.00	43.00
ES	90	10.62	6.64	1.30	31.50
Gini	555	47.02	4.59	32.73	57.68
Poor	280	3.69	0.94	0.80	6.10
Rich	280	39.54	3.99	30.20	49.00
Informal	255	43.98	16.00	17.75	81.45
VoteBuying	237	2.36	0.99	0.14	3.86
Favouritism	161	2.71	0.69	1.48	4.63
Monopoly	161	3.61	0.64	2.31	5.17
Openness	805	56.15	29.32	10.34	165.30
Primary	612	21.57	8.74	4.78	42.05
Secondary	612	17.44	8.56	2.79	48.07
Natural	826	4.14	4.60	0.06	27.68
Government	798	12.20	4.12	2.98	43.48
MinWage	630	123.80	58.11	28.30	479.40
GDP	826	7.61	0.92	5.40	9.73

Note: column 1 shows the number of observations; column 2 the mean; column 3 the standard deviation; column 4 the minimum value; and column 5 the maximum value.

Table 2. Perceived corruption and income inequality.

	Gini					Income Poor	Income Rich
VARIABLES	(1) GLLAMM	(2) GLLAMM	(3) GLLAMM	(4) IV	(5) IV	(6) GLLAMM	(7) GLLAMM
BCI	-0.081***	-0.045***		-0.310***		0.002	-0.051***
	(0.016)	(0.015)		(0.071)		(0.006)	(0.019)
CCI			-0.504***		-4.664***		
			(0.122)		(1.130)		
Informal		-0.040***	-0.044***	-0.055***	-0.035*	0.009**	-0.088***
		(0.013)	(0.009)	(0.018)	(0.021)	(0.004)	(0.013)
Openness	-0.000	-0.024***	-0.012*	-0.006	-0.000	0.009***	-0.025***
	(0.004)	(0.008)	(0.007)	(0.010)	(0.012)	(0.002)	(0.006)
Government	0.346***	0.489***	0.567***	0.412***	0.378***	-0.148***	0.440***
	(0.051)	(0.053)	(0.034)	(0.086)	(0.104)	(0.012)	(0.032)
Natural	-0.056**	0.057**	0.069**	0.070	0.060	-0.041**	-0.015
	(0.024)	(0.028)	(0.028)	(0.050)	(0.052)	(0.018)	(0.027)
Primary	-0.073***	-0.034*	-0.071***	-0.094***	-0.054	-0.020***	-0.009
	(0.026)	(0.019)	(0.017)	(0.032)	(0.038)	(0.006)	(0.021)
Secondary	0.011	0.011	-0.032	0.066*	0.052	0.030**	0.021
	(0.048)	(0.046)	(0.050)	(0.038)	(0.043)	(0.015)	(0.040)
MinWage	-0.015***	-0.010*	-0.017***	-0.001	-0.009	0.002**	-0.014***
	(0.004)	(0.006)	(0.005)	(0.006)	(0.007)	(0.001)	(0.003)
GDP	-1.586***	-4.188***	-3.808***	-5.944***	-6.350***	0.964***	-4.284***
	(0.495)	(0.458)	(0.474)	(0.610)	(0.770)	(0.111)	(0.541)
Constant	63.881***	82.435***	78.578***	110.890***	98.606***	-3.771***	79.157***
	(3.013)	(4.637)	(3.802)	(8.127)	(6.685)	(1.391)	(5.867)
Basmann chi2				0.599	0.000		
(p-value)				(0.4387)	(0.9955)		
Sargan (score) chi2				0.625	0.000		
(p-value)				(0.4289)	(0.9954)		
Durbin (score) chi2				26.546	24.531		
(p-value)				(0.0000)	(0.0000)		
Wu-Hausman F test				28.401	26.2742		
(p-value)				(0.0000)	(0.0000)		
Cragg-Donald Statistic				18.407	15.5548		
Observations	486	249	215	249	215	233	233
R-squared				0.294	0.207		

Note: Robust standard errors in parenthesis for GLLAMM models. *** p<0.01, ** p<0.05, * p<0.1.
Columns 4 and 5 are estimated using the IV technique; the remaining columns use the GLLAMM technique. Columns 1 to 5 use the net Gini index as dependent variable; column 6 uses the income share held by the poorest 20 percent of the population; and column 7 uses the income share held by the richest 10 percent of the population. Columns 1, 2, 4, 6, and 7 use the Bayesian estimate of corruption, *BCI*, as a corruption measure; columns 3 and 5 use *CCI*, a more traditional corruption index.

Table 3. Individual-level experienced corruption and income inequality.

	Gini		Income Poor	Income Rich
VARIABLES	(1)	(2)	(3)	(4)
GCB	-0.107***	-0.028**	0.015***	-0.076***
	(0.017)	(0.013)	(0.006)	(0.026)
Informal		-0.094***	0.009***	-0.108***
		(0.005)	(0.002)	(0.009)
Openness	-0.002	-0.027***	0.003***	-0.058***
	(0.006)	(0.006)	(0.001)	(0.008)
Government	0.076	0.430***	-0.105***	0.508***
	(0.081)	(0.044)	(0.013)	(0.041)
Natural	0.069	0.060***	-0.077***	0.116***
	(0.056)	(0.013)	(0.004)	(0.033)
Primary	-0.094***	-0.153***	-0.020***	-0.106***
	(0.030)	(0.013)	(0.004)	(0.020)
Secondary	-0.016	-0.071*	0.026***	0.041
	(0.055)	(0.040)	(0.003)	(0.037)
MinWage	-0.015***	-0.012***	0.000	-0.014***
	(0.005)	(0.003)	(0.001)	(0.004)
GDP	-2.496***	-3.652***	0.904***	-3.915***
	(0.324)	(0.392)	(0.069)	(0.499)
Constant	72.766***	83.290***	-2.800***	77.073***
	(2.965)	(3.121)	(0.848)	(4.966)
Observations	111	106	81	81

Note: all models were estimated using the GLLAMM method. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.
GCB measures corruption experienced by individuals. As dependent variables, columns 1 and 2 use the net Gini index; column 3 uses the income share held by the poorest 20 percent; and column 4 uses the income share held by the richest 10 percent.

Table 4. Firm-level experienced corruption and income inequality.

	Gini		Income Poor	Income Rich
VARIABLES	(1)	(2)	(3)	(4)
ES	0.043***	0.083***	-0.022***	0.110***
	(0.009)	(0.013)	(0.004)	(0.021)
Informal		-0.088***	0.007***	-0.115***
		(0.007)	(0.002)	(0.009)
Openness	0.026***	0.022***	-0.001	0.022***
	(0.003)	(0.002)	(0.001)	(0.006)
Government	0.420***	0.546***	-0.111***	0.643***
	(0.037)	(0.019)	(0.009)	(0.035)
Natural	0.240***	0.136***	-0.062***	0.122***
	(0.018)	(0.019)	(0.006)	(0.032)
Primary	-0.007	-0.159***	-0.027***	0.013
	(0.012)	(0.010)	(0.003)	(0.018)
Secondary	-0.008	-0.117***	0.008*	-0.148***
	(0.019)	(0.023)	(0.004)	(0.033)
MinWage	-0.025***	-0.010***	0.004***	-0.027***
	(0.003)	(0.002)	(0.000)	(0.002)
GDP	-2.363***	-2.962***	0.805***	-2.385***
	(0.129)	(0.216)	(0.063)	(0.457)
Constant	61.327***	73.002***	-1.093	58.834***
	(1.177)	(1.935)	(0.679)	(3.853)
Observations	89	84	64	64

Note: all models were estimated using the GLLAMM method. Robust standard errors in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
ES measures corruption experienced by firms. As dependent variables, columns 1 and 2 use the net Gini index; column 3 uses the income share held by the poorest 20 percent; and column 4 uses the income share held by the richest 10 percent.

Table 5. Experienced corruption and income inequality: vote buying, informal markets, firm-favouritism and monopoly.

	Gini					
VARIABLES	(1) GLAMM	(2) FE	(3) BMA	(4) GLAMM	(5) FE	(6) BMA
GCB	0.008	0.384**	-0.011			
	(0.106)	(0.169)	(0.238)			
GCB*VoteBuying	0.056	-0.077	0.011			
	(0.047)	(0.050)	[0.19]			
VoteBuying	-1.078	4.561**	-0.003			
	(0.881)	(1.955)	[0.18]			
GCB*Informal	-0.005**	-0.009**	-0.004			
	(0.002)	(0.003)	[0.55]			
Informal	-0.032	0.232**	-0.025	-0.079***	-0.011	-0.061*
	(0.031)	(0.089)	[0.31]	(0.008)	(0.031)	(0.031)
ES				-0.126	-0.563***	0.202
				(0.088)	(0.183)	(0.178)
ES*Favouritism				0.112***	0.201**	0.003
				(0.035)	(0.072)	[0.13]
Favouritism				1.648***	2.222**	1.467
				(0.186)	(0.873)	[0.73]
ES*Monopoly				-0.022	-0.019	0.005
				(0.036)	(0.068)	[0.16]
Monopoly				1.185***	-0.476	1.394
				(0.314)	(0.952)	[0.59]
Openness	0.050***	0.001	0.023	-0.020***	-0.007	-0.023
	(0.010)	(0.087)	(0.050)	(0.003)	(0.011)	(0.017)
Government	0.504***	-0.362	0.543	0.426***	0.264	0.458***
	(0.087)	(0.357)	(0.314)	(0.028)	(0.180)	(0.159)
Natural	0.080	0.158	-0.061	0.075***	0.221***	0.132**
	(0.052)	(0.158)	(0.104)	(0.016)	(0.060)	(0.058)
Primary	-0.190***	0.100	-0.293***	-0.114***	0.065	-0.039
	(0.033)	(0.149)	(0.085)	(0.012)	(0.088)	(0.051)
Secondary	-0.095***	-0.018	-0.011	-0.035**	-0.034	-0.069
	(0.029)	(0.097)	(0.115)	(0.014)	(0.055)	(0.066)
MinWage	-0.009**	-0.000	-0.012	-0.008***	-0.008	-0.011
	(0.004)	(0.006)	(0.013)	(0.001)	(0.005)	(0.008)
GDP	-3.908***	-3.193***	-4.157**	-4.726***	-3.729***	-4.422***
	(0.807)	(0.904)	(1.795)	(0.182)	(0.663)	(0.815)
Constant	76.707***	78.463***	85.580***	79.002***	69.003***	73.939***
	(4.935)	(10.476)	(16.241)	(1.771)	(4.357)	(7.794)
	-0.297**			-0.410***		
	(0.135)			(0.078)		
	2.354***			1.783***		
	(0.229)			(0.054)		
Observations	81	81	81	84	84	84
R-squared		0.920			0.804	
Number of id		12			17	

Note: all models were estimated using net Gini as dependent variable. Models 1 and 4 were estimated using the GLLAMM method; models 2 and 5 were estimated using the Fixed Effects method; and columns 3 and 6 use the BMA method. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Columns 1 to 3 use corruption experienced by individuals; columns 4 to 6 estimate the models using corruption experienced by firms. Columns 1 to 3 use the variable *voteBuying* which represents vote buying, an interaction, *GCB*VoteBuying*, between *voteBuying* and individual-level experienced corruption, and an interaction variable, *GCB*informal*, between the size of informal markets and individual-level corruption. Columns 4 to 6 use the variable *favouritism* which represents the degree to which the decisions of government officials show preference for well-connected firms and individuals when deciding upon policies and contracts and *monopoly* that represents the degree to which government anti-monopoly policies promote competition between companies. *ES*Favouritism* is the interaction between *ES* and *favouritism*, and *ES*Monopoly* is the interaction between *ES* and *monopoly*.

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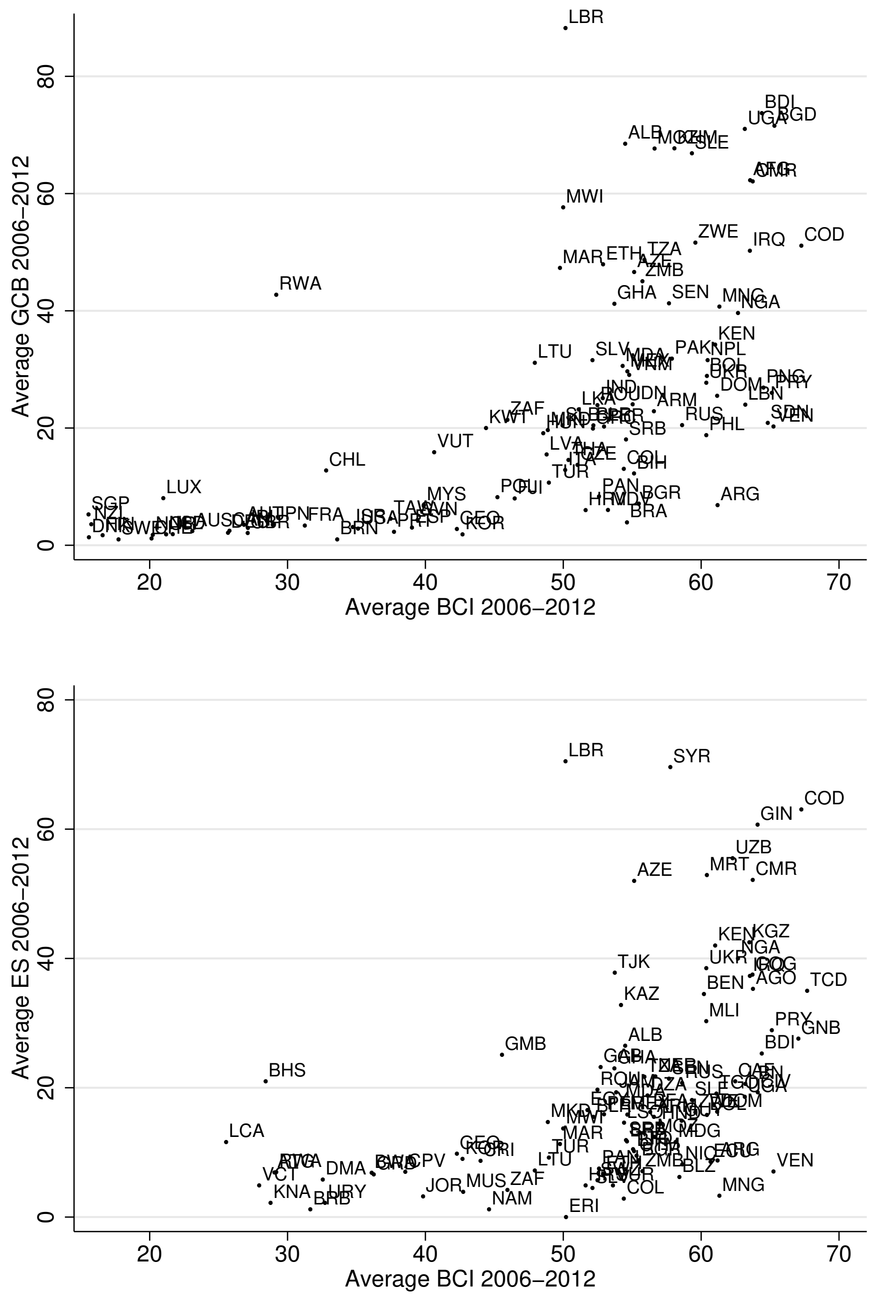

Figure 1. Perceived corruption (BCI), and corruption experienced at individual (GCB) and firm levels (ES). Sources: Standaert (2015), Transparency International (2013) and World Bank (2017b).

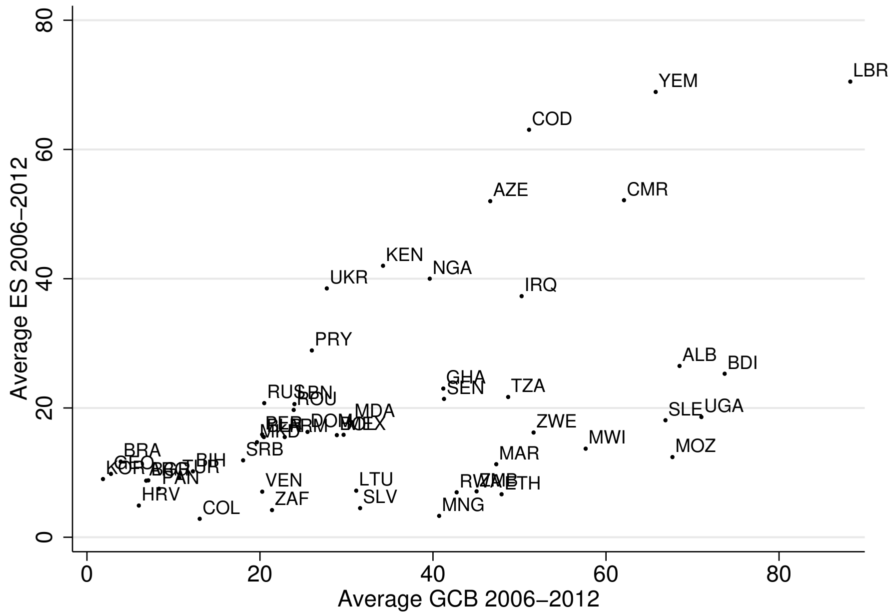

Figure 2. Corruption experienced by individuals (Global Corruption Barometer) and corruption experienced by firms (Bribery Incidence, Enterprise Surveys). Sources: Transparency International (2013) and World Bank (2017b).

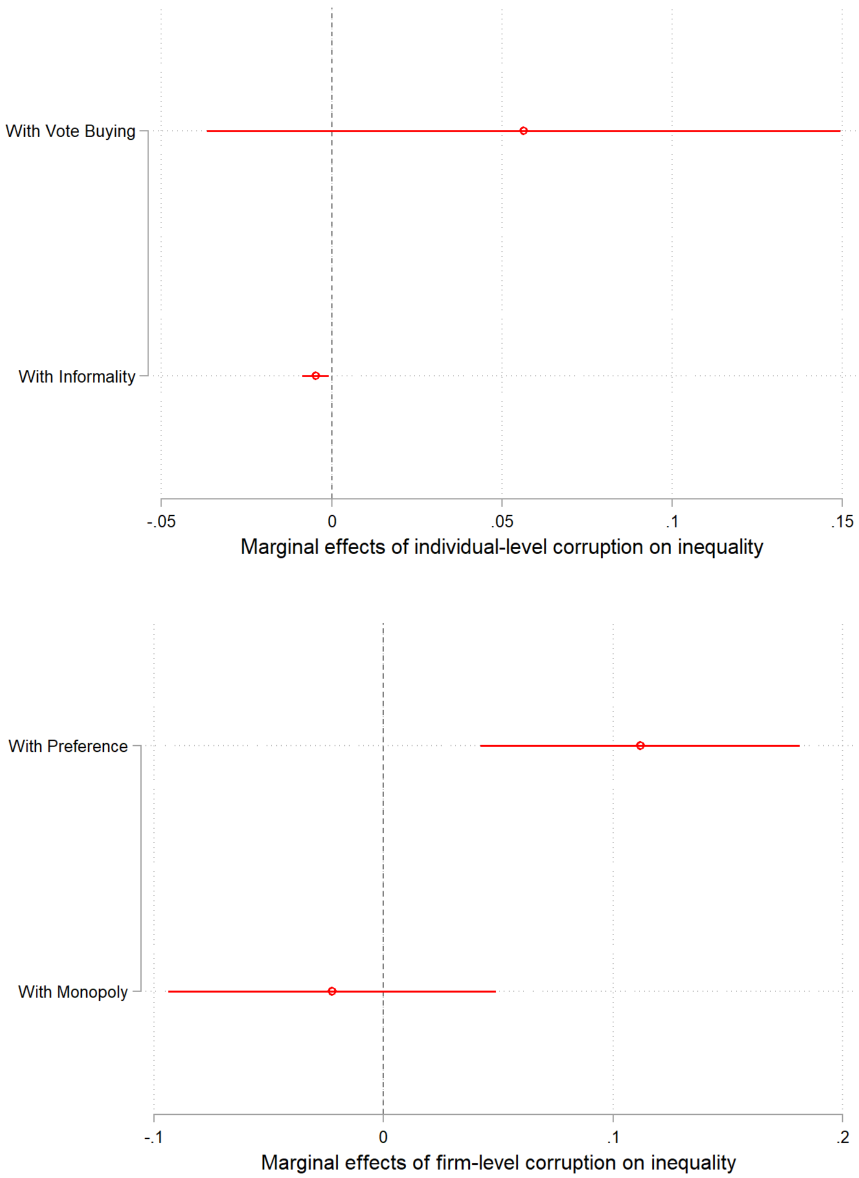

Figure 3. Marginal effects of experienced corruption on inequality. Based on the results of the GLLAMM estimates in Table 5 (columns 1 and 4).