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Corruption, Income Inequality, and Poverty in the United States

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Corruption, Income Inequality, and Poverty in the United States

Summary

In this study we analyze the effects of corruption on income inequality and poverty. Our analysis advances the existing literature in four ways. First, instead of using corruption indices assembled by various investment risk services, we use an objective measure of corruption: the number of public officials convicted in a state for crimes related to corruption. Second, we use all commonly used inequality and poverty measures including various Atkinson indexes, Gini index, standard deviation of the logarithms, relative mean deviation, coefficient of variation, and the poverty rate defined by the U.S. Census Bureau. Third, we minimize the problems which are likely to arise due to data incomparability by examining the differences in income inequality, and poverty across U.S. states. Finally, we exploit both time series and cross sectional variation in the data. We find robust evidence that an increase in corruption increases income inequality and poverty.

Keywords: Corruption, Income Inequality, Poverty

JEL Classification: D31, D73, I32

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1. Introduction

An increasing number of empirical studies (e.g. Mauro 1995, Knack and Keefer 1995, Knack 1996, Keefer and Knack 1997, Mo 2001, Pellegrini and Gerlagh 2004) present persuasive evidence regarding the detrimental effects of corruption on various economic variables such as the growth rate of income.

Corruption does not only affect the growth rate of income but also affects income inequality and poverty. “The benefits from corruption are likely to accrue to the better connected individuals ... who belong mostly to high income groups” (Gupta et. al. 2002, 23). According to Jonston (1989), corruption favors the ‘haves’ rather than the ‘have nots’ particularly if the stakes are large. The burden of corruption falls disproportionately on low income individuals. Individuals who belong to low income groups pay a higher proportion of their income than the individuals who belong to high income groups. As Tanzi (1998) argues, corruption distorts the redistributive role of government. Since only the better connected individuals get the most profitable government projects, it is less likely that the government is able to improve the distribution of income and make the economic system more equitable. It diverts government spending away from projects that benefit mostly low income individuals such as education and health to, for example, defense projects that create opportunities for corruption (Chetwyn et al. 2003).

Nevertheless, there are only a few empirical studies (Li, Xu, and Zou 2000, Gupta et. al. 2002, and Chong and Calderon 2000a and 2000b) analyzing the effects of corruption on income inequality and poverty. Using data from a mixed group of countries, i.e., low,

middle, and high-income, Li, Xu, and Zou (2000) and Chong and Calderon (2000a) find an inverse U-shaped relationship between corruption and income inequality. They find a positive relationship between corruption and income inequality in high-income countries and a negative relationship in low-income countries. Gupta et al. (2002), on the other hand, using a smaller sample of countries, find a positive and linear relationship between corruption and income inequality. Chong and Calderon (2000b) and Gupta et al. (2002) both analyze the effects of corruption on poverty as well as on income inequality. As Chong and Calderon (2000b) argue, an increase in income inequality as corruption increases does not necessarily mean that poverty also increases. If, for example, the incomes in the higher end of the distribution grow faster than incomes in the lower end of the distribution, income inequality increases while poverty decreases. Both Chong and Calderon (2000b) and Gupta et al. (2002) find a positive and linear relationship between corruption and poverty.

In this study, we analyze the effects of corruption on income inequality and poverty by using data from U.S. states. Using data from U.S. states is quite advantageous. The likelihood of the problems arising due to data incomparability is minimal. Data on corruption as well as on income inequality and poverty for U.S. states are more comparable than those for different countries, and U.S. states are more similar in other dimensions that are difficult to measure. We find robust evidence that an increase in corruption increases income inequality and poverty across U.S. states.

Our analysis advances the existing literature in three ways. First, instead of using subjective cross-country corruption indices assembled by various investment risk services, we use an objective measure of corruption: the number of government officials

convicted in a state for crimes related to corruption. Second, we employ all commonly used inequality and poverty measures including various Atkinson indexes, Gini index, standard deviation of the logarithms, relative mean deviation, coefficient of variation, and the poverty rate defined by the U.S. Census Bureau. Finally, we exploit both time series and cross-sectional variation in the data.

2. Data

We use annual data from 50 states for 17 years, from 1981 to 1997. For our measure of corruption (*Corruption*), we use the number of government officials convicted in a state for crimes related to corruption in a year. The data are from the Justice Department's "Report to Congress on the Activities and Operations of the Public Integrity Section". These data are used by several studies such as Goel and Rich (1989), Fisman and Gatti (2002), Fredriksson, List and Millimet (2003) and Glaeser and Saks (2006) to measure corruption across states. They cover a broad range of crimes from election fraud to wire fraud. We deflate the number of convictions by state population. As Glaeser and Saks (2006) argue, using the number of convictions creates a problem since a smaller number of government officials are likely to be convicted in corrupt states. Following Glaeser and Saks (2006), to mitigate this problem, we focus on federal convictions.

We measure income inequality across states by using the four traditional measures Gini Index (*Gini*), standard deviation of the logarithms (*SDL*), relative mean deviation (*RMD*), and the coefficient of variation (*CV*) as well as the various Atkinson

indexes (I_ϵ) given by Wu, Golan, and Perloff (2006)¹. As mentioned by Wu, Golan, and Perloff (2006), all of these measures are scale free relative measures. Following Sen (1997), if we consider distributions of income over persons, $i = 1, 2, 3, \dots, n$, and let y_i be the income of person i , and the average level of income be μ , the four traditional measures are²

$$Gini = \left(\frac{1}{2} n^2 \mu \right) \sum_{i=1}^n \sum_{j=1}^n |y_i - y_j|$$

$$SDL = \left[\frac{\sum_{i=1}^n (\log \mu - \log y_i)^2}{n} \right]^{1/2}$$

$$RMD = \sum_{i=1}^n |\mu - y_i| n \mu;$$

and

$$CV = \frac{V^{1/2}}{\mu}.$$

Atkinson index (I) is an inequality measure which is based on the concept of what Atkinson (1970) calls the equally distributed equivalent level of income.³ It is

$$I_\epsilon = \begin{cases} 1 - \left[\frac{1}{n} \sum_{i=1}^n \left(\frac{y_i}{\mu} \right)^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}} & \text{if } \epsilon \neq 1 \\ 1 - \left[\prod_{i=1}^n \left(\frac{y_i}{\mu} \right) \right]^{\frac{1}{n}} & \text{if } \epsilon = 1, \end{cases}$$

¹ We wish to thank Ximing Wu, Jeffrey M. Perloff, and Amos Golan for making their data publicly available.

² $V = \frac{\sum_{i=1}^n (\mu - y_i)^2}{n}$

³ See Atkinson (1970), Sen (1997), and Wu, Perloff, and Golan (2006a) for an excellent discussion of the Atkinson index as well as the traditional inequality measures.

where, ε measures the degree of inequality aversion. It takes values ranging from 0 to ∞ . As ε increases the Atkinson index becomes more sensitive to changes at the lower end of the income distribution and as ε decreases it becomes more sensitive to changes at the higher end of the distribution. The index equals zero when distribution of income is equal and approaches 1 as inequality increases. We assume ε is equal to 0.5, 1, and 1.5.⁴ We measure poverty by the percentage of people whose income is under the poverty threshold given by the Census Bureau. In order to determine the number of people who are in poverty, the Census Bureau uses a set of income thresholds that vary by the size and the composition of the family. If a family's total income is less than the family's threshold, then every person belonging to that family is considered in poverty. The poverty thresholds are updated using the consumer price index.

Based on the averages across the 17 years, Texas has the highest inequality regardless of which inequality measure is used while Mississippi has the highest poverty. Vermont has the lowest inequality when SDL is used to measure inequality while Wisconsin has the lowest inequality when other measures are used. New Hampshire has the lowest poverty. Mississippi and Vermont are the most and the least corrupt states, respectively. The states with the three lowest and highest inequality and poverty as well those with the three lowest and highest corruption are given in Table 1. The summary statistics for all of the inequality measures, poverty, and corruption are given in Table 2.

As expected, the correlations between the inequality measures, poverty, and corruption are positive: the correlation coefficients between corruption and the inequality measures are around 0.20 as is the correlation coefficient between corruption and

⁴ Atkinson (1970) assumes ε lies within the range of (0, 2.5]. The index is given for 0.1, 0.5, 1, 1.5, 2, and 2.5 by Wu, Perloff, and Golan (2006a). Nevertheless, to save space we do not report the results for 0.1, 2, and 2.5.

poverty. Pairwise correlations of the inequality measures, poverty, and corruption are given in Table 3.

We include a set of control variables in our regressions to minimize the omitted variable bias. First, following Wu, Perloff, and Golan (2006), we include a set of government policy variables: earned income tax credit benefit rate (*EITCB*), earned income tax credit phase-out rate (*EITCP*), and aid to the families with dependent children/temporary assistance to needy families (*AFDC/TANF*). The *AFDC/TANF* is the maximum monthly benefits for a single parent, three person family. *EITCB* is the product of the earned income tax credit rate and the maximum income required for maximum benefit. The earned income tax credit is phased out as a family's income rises. *EITCP* is the rate at which the earned income tax credit benefit is reduced over the phase-out range. The data are from Wu, Perloff, and Golan (2006). Second, we include two macroeconomic variables: real per capita personal income (*Income*) and the unemployment rate (*Unemployment*). The income data are from the Bureau of Economic Analysis (BEA) and the unemployment data are from Bureau of Labor Statistics (BLS). As Glaeser (2005) argues, stronger unions generally mean increased equality. Hence we include the unionization rate (*Union*) as another control variable using the estimates provided by Hirsch, Macpherson, and Vroman (2001). Finally, we include education (*Education*) as our last control variable. We measure education as the share of secondary school enrolment in the population. The data are from National Center for Education Statistics.

3. Results

Corruption and income inequality

To analyze the relationship between corruption and income inequality, we estimate the following basic model by ordinary least squares (OLS) controlling for time and region fixed effects:

$$Inequality_{st} = \alpha + \beta \cdot Corruption_{st} + \gamma \cdot X_{st} + \mu \cdot T_t + \phi \cdot R_s + u_{st}$$

where $Inequality_{st}$ represents each of our measures of income inequality in state s during period t . $Corruption_{st}$ represents corruption whereas X_{st} represents the set of control variables that affect income inequality (*EITCB*, *EITCP*, *AFDC/TANF*, *Education*, *Income*, *Unemployment*, *Union*), T_t represents the set of year dummies, R_s represents the set of region dummies and u_{st} represents the error term. The results of OLS estimation are given in Table 4. The R^2 ranges from 0.46 to 0.64. In all regressions, the estimated coefficient of corruption is positive and highly significant indicating that corruption increases income inequality. One standard deviation increase in *Corruption* increases *Gini*, for example, by 0.3 percentage points, the same increase in *Gini* due to a 20 percent decrease in *AFDC/TANF*. Up to 6 percent of the difference in Gini index between the least corrupt state Vermont and the most corrupt state Mississippi is explained by different corruption levels in those states. Similarly, one standard deviation increase in *Corruption* increases *SDL* by 0.6 percentage points, *RMD* by 0.5 percentage points, and *CV* by 1.4 percentage points.

As mentioned earlier, as ε increases, the Atkinson index becomes more sensitive to changes at the lower end of the income distribution. The estimated coefficient of

Corruption increases as ε increases, indicating that effects of corruption on the lower end of the distribution are higher. One standard deviation increase in *Corruption* increases $I_{\varepsilon=0.5}$, $I_{\varepsilon=1}$, and $I_{\varepsilon=1.5}$, by 0.2, 0.4, and 0.6 percentage points, respectively.

Our results about the effects of macroeconomic and demographic control variables on income inequality are mostly consistent with the earlier studies. The estimated coefficients of *Unemployment*, *Income*, *Education*, and *Union* are significant in all estimations. We find that education and unionization have an equalizing effect while unemployment rate tends to increase income inequality as expected (Li et. al. 2000, Gupta et. al. 2002, Glaeser 2005, Wu, Perloff, and Golan 2006). According to our estimations, an increase in real per capita income increases income inequality. Regarding the government policy variables, the estimated coefficients of *EITCB*, *EITCP*, *AFDC/TANF* are significant in all estimations. Again, as expected, while the estimated coefficient of *EITCP* is positive, the estimated coefficients of both *EITCB* and *AFDC/TANF* are negative (Wu, Perloff, and Golan 2006).

Corruption and poverty

In our poverty regressions we control for *Income*, *Education*, *Unemployment*, region and year dummies, as well as inequality (*Gini*, *SDL*, *RMD*, *CV*, *AI*). The results of the OLS estimation are given in Table 5.⁵ We first estimate a poverty regression without controlling for inequality. The R^2 is 0.67. The estimated coefficient of corruption is positive and significant indicating that corruption increases poverty. One standard deviation increase in *Corruption* increases *Poverty* by 0.5 percentage points, the same

⁵ In the second column we give the results of the regression in which we measure inequality by *Gini*, third by *SDL*, fourth by *RMD*, fifth by *CV*, sixth by $I_{\varepsilon=0.5}$, seventh by $I_{\varepsilon=1}$, and eighth by $I_{\varepsilon=1.5}$.

increase in *Poverty* due to a 10 percent increase in *Unemployment*. Up to 7 percent of the difference in *Poverty* between Vermont and Mississippi is explained by different corruption levels in those states. According to Ravallion (1997), income inequality matters for poverty reduction. It is then quite likely that corruption affect poverty both directly and indirectly through income inequality. In our regressions the coefficient of the income inequality regardless of the measure we use is positive and highly significant which is consistent with Chong and Calderon (2000b). When we include income inequality in our poverty regressions the R^2 increases significantly. It ranges from 0.74 to 0.82. In all regressions, the estimated coefficient of corruption is positive and highly significant. Nevertheless the coefficient estimate decreases when we include inequality indicating that corruption has indeed direct effects on poverty as well as indirect effects through income inequality. Regarding the other control variables, we find a positive relationship between *Unemployment* and *Poverty* and consistent with both Chong and Calderon (2000b) and Gupta et al. (2002) a negative relationship between *Income* and *Poverty*. According to our estimations, there is an inverse U-shaped relationship between *Education* and *Poverty*.

4. Robustness of the Results

The main robustness issue is whether the results are due to reverse causality. As You and Khagram (2005), Uslaner (2006), and Chong and Gradstein (2007) argue, high income inequality and high poverty are likely to lead to more corruption. Instrumental variables (IV) estimation helps address this problem. The choice of the instrument is extremely important. A good instrument is a variable that is supposed to be uncorrelated

with the error term but correlated with the endogenous variable *Corruption*. Previous studies such as Mauro (1995) use instruments such as ethnic fractionalization index (*EFI*). The index is calculated as

$$EFI_s = 1 - \sum_{p=1}^P n_{sp}^2,$$

where n_{sp} is the population share of group p in country s . *EFI* gives us the probability that two randomly selected individuals in a country belong to two different ethnic groups. It reaches a maximum if every individual in a country belongs to a different ethnic or religious group. In our regressions we use both ethnic and religious fractionalization indexes as our instruments. The data we use to calculate the *EFI* are from the Census Bureau for 1970, which cover five ethnic groups: Whites, Blacks, American Indian and Eskimos, Asians, and Others. The data we use to calculate the religious fractionalization index (*RFI*) are from the American Religion Data Archive for the same year. These data are collected by representatives of the Association of Statisticians of American Religious Bodies to provide information on the number of churches and members for 53 Judeo-Christian church bodies for 1971 representing an estimated 81 percent of church membership in the United States. The results of the IV estimation for the inequality regressions are given in Table 6, and for the poverty regressions in Table 7. The estimated coefficient of corruption is positive and highly significant in all regressions indicating that our results are robust to reverse causality. As long as the ethnic and religious fractionalization indexes affect income inequality and poverty through *Corruption*, the instruments are theoretically valid. According to the 1st stage F and the Hansen J statistics given in Table 6 and Table 7, they are empirically valid as well.

The second robustness issue is the possible measurement error in *Corruption*.

Nevertheless, IV estimation does not only help correct for reverse causality but also the measurement error.

The third robustness issue is the presence of spatial autocorrelation. Income inequality and poverty in a state is likely to be affected by income inequality and poverty in neighboring states. Ignoring spatial autocorrelation in income inequality and poverty causes biased estimates. To control for spatial autocorrelation, we estimate the following spatial autoregressive (i.e., spatial lag) model by maximum likelihood (ML):

$$Inequality_{st} (Poverty_{st}) = \alpha + \beta \cdot Corruption_{st} + \gamma \cdot X_{st} + \rho \cdot W \cdot Inequality_{st} (Poverty_{st}) + \mu \cdot T_t + \phi \cdot R_s + u_{st}$$

where, W is the spatial-lag weighting matrix and ρ is the coefficient giving the sign and the strength of spatial autocorrelation in *Inequality (Poverty)*. We adopt a simple weighting scheme of strict state contiguity, such that $w_{ij} = 1$ if $i \neq j$ and state i is contiguous to state j and $w_j = 0$ otherwise. $W \cdot Inequality_{st} (Poverty_{st})$ is nothing but the average income inequality (poverty) in state s 's neighboring states at time t . The results of the ML estimation are given in Tables 8 and 10. Spatial autocorrelation is present in some poverty regressions and in all inequality regressions. The coefficient estimates are virtually the same as the ones estimated by OLS. We estimate our spatial autoregressive model of inequality and poverty by instrumenting *Corruption* with ethnic and religious fractionalization indexes for 1970 and 1971 as well. The results are given in Tables 9 and 11. The estimated coefficients of *Corruption* are again positive and significant in all regressions.

The fourth robustness issue is the presence of outliers. We estimate the regressions without the observations identified as outliers by Hadi's methodology. The results are given in Tables 12 and 13. The estimated coefficient of *Corruption* remains positive and significant in all estimations. It increases slightly in all estimations. One standard deviation increase in *Corruption* increases *Gini*, for example, by 0.4 percentage points and *Poverty* by 0.6 percentage points when we exclude outliers. The partial regression plots between *Corruption* and our income inequality measures as well as *Corruption* and *Poverty* are given in Figures 1 through 8.

The fifth and the last robustness issue is the stationarity of our inequality and poverty measures. We use two commonly used unit root tests for panel data: Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS). Under the null hypothesis, both tests assume that all series in the panel are non-stationary. LLC test assumes that all series are stationary under the alternative hypothesis whereas IPS test assumes that only a fraction of the series in the panel is stationary. Using both tests we reject the null hypothesis of non-stationarity of our inequality and poverty measures.

5. Conclusion

Corruption is not a phenomenon peculiar to low-income countries. It is possible to find examples of corruption in high-income countries as well. In Germany, for example, corruption led to an increase in cost of about 20 to 30 percent during the construction of terminal 2 at Frankfurt Airport. In Italy, the cost of major construction projects fell significantly in the aftermath of corruption investigations in the early 1990s (Rose-Ackerman 1999). It is not a new phenomenon either. Prior to the New Deal, welfare

programs in the U.S. were administered by local governments which were almost always associated with corruption. In 1933, when unemployment reached 25 percent, the federal government introduced welfare programs which redistributed 4 percent of the gross national product to millions of families. Knowing that he would incur enormous losses if the New Deal were perceived as corrupt, President Roosevelt took the fight against corruption in the administration of welfare programs very seriously by establishing offices to investigate complaints of corruption which led to vigorous prosecution of corrupt government officers (Wallis, Fishback, and Kantor 2006).

In this study, we analyze the effects of corruption on income inequality and poverty by using data from U.S. states. To our knowledge, this is in fact the first study using data from U.S. states. Where previous analyses relied on cross-sectional variation in cross-country data, our analysis is less sensitive to bias due to unobserved country-specific heterogeneity. Of course, data on our variables of interest - corruption, income inequality and poverty – as well as on control variables such as *AFDC/TANF*, are more comparable across U.S. states than those across different countries. We find robust evidence that an increase in corruption increases income inequality and poverty. One standard deviation increase in corruption increases Gini index by 0.3 percentage points, the standard deviation of the logarithms by 0.6 percentage points, the relative mean deviation by 0.5 percentage points, the coefficient of variation by 1.4 percentage points, and poverty by 0.5 percentage points.

Using Atkinson indexes with different degrees of inequality aversion helps us see if the effects of corruption on the lower end of the distribution differ from the effects on the higher end. We find that the coefficient estimate of corruption increases as the degree

of inequality aversion increases, indicating that effects of corruption on the lower end of the distribution are higher. One standard deviation increase in corruption increases the Atkinson indexes by 0.2, 0.4, and 0.6 percentage points for the degrees of inequality aversion 0.5, 1, and 1.5, respectively.

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Table 1. Worst and Best Three States

	<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	$I_{\epsilon=0.5}$	$I_{\epsilon=1}$	$I_{\epsilon=1.5}$	<i>Poverty</i>	<i>Corruption</i>
Worst 3 States	TX	TX	TX	TX	TX	TX	TX	MS	MS
	MS	LA	MS	LA	LA	LA	LA	LA	TN
	LA	MS	LA	MS	MS	MS	MS	NM	SD
Best 3 States	WI	VT	WI	WI	WI	WI	WI	NH	VT
	VT	WI	UT	VT	VT	VT	VT	CT	OR
	UT	UT	VT	ME	UT	UT	UT	NJ	WA

Table 2. Summary Statistics of Inequality Measures, Poverty Rate, and Corruption

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>Gini</i>	850	0.34	0.03	0.26	0.45
<i>SDL</i>	850	0.67	0.11	0.48	1.60
<i>RMD</i>	850	0.48	0.05	0.36	0.64
<i>CV</i>	850	0.55	0.12	0.28	1.01
$I_{\epsilon}=0.050$	850	0.09	0.02	0.05	0.17
$I_{\epsilon}=0.100$	850	0.19	0.03	0.11	0.31
$I_{\epsilon}=0.150$	850	0.29	0.05	0.17	0.46
<i>Poverty</i>	850	0.14	0.04	0.02	0.27
<i>Corruption</i>	850	0.31	0.30	0	2.19

Table 3. Pairwise Correlations of the Inequality Measures, Poverty Rate, and Corruption

	<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	$I_{\epsilon}=0.5$	$I_{\epsilon}=1$	$I_{\epsilon}=1.5$	<i>Poverty</i>	<i>Corruption</i>
<i>Gini</i>	1.00								
<i>SDL</i>	0.86	1.00							
<i>RMD</i>	0.99	0.82	1.00						
<i>CV</i>	0.91	0.69	0.91	1.00					
$I_{\epsilon}=0.50$	0.99	0.89	0.98	0.92	1.00				
$I_{\epsilon}=0.100$	0.98	0.82	0.98	0.97	0.99	1.00			
$I_{\epsilon}=0.150$	0.93	0.74	0.93	0.99	0.95	0.98	1.00		
<i>Poverty</i>	0.56	0.31	0.60	0.59	0.54	0.58	0.58	1.00	
<i>Corruption</i>	0.19	0.09	0.20	0.20	0.18	0.19	0.20	0.20	1.00

Table 4. Inequality and Corruption : OLS Estimation
Dependent Variables: Gini, SDL, RMD, CV, and Atkinson Indices

	<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	<i>I_ε=0.5</i>	<i>I_ε=1</i>	<i>I_ε=1.5</i>
<i>Corruption</i>	0.011 (0.002)***	0.019 (0.006)***	0.017 (0.004)***	0.047 (0.011)***	0.006 (0.001)***	0.013 (0.003)***	0.019 (0.004)***
<i>EITCB</i>	-2.191 (1.136)*	-6.937 (3.281)**	-3.059 (1.708)*	-8.892 (5.174)*	-1.411 (0.664)**	-2.614 (1.301)**	-3.604 (2.128)*
<i>EITCP</i>	2.163 (1.137)*	6.854 (3.282)**	3.019 (1.710)*	8.790 (5.176)*	1.395 (0.665)**	2.586 (1.302)**	3.562 (2.128)*
<i>AFDC/TANF</i>	-0.056 (0.011)***	-0.170 (0.038)***	-0.083 (0.016)***	-0.134 (0.044)***	-0.031 (0.006)***	-0.053 (0.012)***	-0.061 (0.018)***
<i>Education</i>	-0.807 (0.182)***	-2.717 (0.543)***	-1.216 (0.281)***	-1.783 (0.848)**	-0.418 (0.106)***	-0.689 (0.211)***	-0.874 (0.333)***
<i>Income</i>	0.002 (0.000)***	0.004 (0.001)***	0.003 (0.000)***	0.009 (0.002)***	0.001 (0.000)***	0.002 (0.000)***	0.004 (0.001)***
<i>Unemployment</i>	0.006 (0.001)***	0.013 (0.001)***	0.010 (0.001)***	0.027 (0.002)***	0.004 (0.000)***	0.007 (0.001)***	0.011 (0.001)***
<i>Union</i>	-0.001 (0.000)***	-0.003 (0.000)***	-0.002 (0.000)***	-0.006 (0.001)***	-0.001 (0.000)***	-0.001 (0.000)***	-0.002 (0.000)***
<i>Constant</i>	1.885 (0.814)**	5.669 (2.346)**	2.636 (1.223)**	6.723 (3.703)*	1.092 (0.476)**	2.026 (0.931)**	2.806 (1.522)*
<i>Time/Region Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	850	850	850	850	850	850	850
Adj. R-squared	0.61	0.64	0.59	0.46	0.60	0.56	0.50

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5. Poverty and Corruption: OLS Estimation
Dependent Variable: Poverty

		<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	$I_{\epsilon=0.5}$	$AI_{\epsilon=1}$	$AI_{\epsilon=1.5}$
<i>Corruption</i>	0.018 (0.003)***	0.009 (0.002)***	0.014 (0.003)***	0.009 (0.002)***	0.010 (0.002)***	0.010 (0.002)***	0.009 (0.002)***	0.009 (0.002)***
<i>Inequality</i>		0.718 (0.033)***	0.156 (0.037)***	0.476 (0.217)***	0.158 (0.009)***	1.216 (0.063)***	0.644 (0.031)***	0.406 (0.021)***
<i>Education</i>	5.548 (1.315)***	4.028 (1.091)***	5.121 (1.178)***	3.724 (1.090)***	3.772 (1.053)***	4.005 (1.054)***	3.699 (1.033)***	3.661 (1.036)***
<i>Education</i> ²	-58.869 (11.751)***	-38.370 (9.959)***	-50.307 (10.677)***	-35.597 (9.949)***	-39.304 (9.445)***	-38.920 (9.528)***	-36.779 (9.310)***	-37.509 (9.244)***
<i>Income</i>	-0.069 (0.004)***	-0.068 (0.003)***	-0.067 (0.004)***	-0.069 (0.003)***	-0.071 (0.003)***	-0.068 (0.003)***	-0.069 (0.003)***	-0.071 (0.003)***
<i>Unemployment</i>	0.008 (0.001)***	0.005 (0.000)***	0.007 (0.001)***	0.005 (0.000)***	0.005 (0.000)***	0.005 (0.000)***	0.005 (0.000)***	0.005 (0.000)***
<i>Constant</i>	0.075 (0.042)*	-0.096 (0.034)***	-0.009 (0.041)	-0.073 (0.034)**	0.072 (0.033)**	0.029 (0.032)	0.036 (0.032)	0.043 (0.033)
<i>Time/Region Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	850	850	850	850	850	850	850	850
R-squared	0.67	0.81	0.74	0.82	0.80	0.80	0.80	0.79

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. Inequality and Corruption: IV Estimation
Dependent Variables: Gini, SDL, RMD, CV, and Atkinson Indices

	<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	$I_{\epsilon=0.5}$	$I_{\epsilon=1}$	$I_{\epsilon=1.5}$
<i>Corruption</i>	0.107 (0.017)***	0.221 (0.042)***	0.169 (0.027)***	0.423 (0.069)***	0.060 (0.009)***	0.118 (0.019)***	0.166 (0.027)***
<i>EITCB</i>	-2.701 (1.375)**	-8.003 (3.377)**	-3.862 (2.069)*	-10.875 (5.496)**	-1.696 (0.775)**	-3.170 (1.488)**	-4.378 (2.174)**
<i>EITCP</i>	2.693 (1.375)**	7.963 (3.379)**	3.854 (2.071)*	10.854 (5.503)**	1.692 (0.775)**	3.165 (1.489)**	4.368 (2.176)**
<i>AFDC/TANF</i>	-0.063 (0.021)***	-0.185 (0.053)***	-0.094 (0.033)***	-0.161 (0.081)**	-0.035 (0.012)***	-0.061 (0.023)***	-0.072 (0.032)**
<i>Education</i>	-0.923 (0.308)***	-2.958 (0.747)***	-1.398 (0.482)***	-2.231 (1.242)*	-0.482 (0.175)***	-0.815 (0.339)**	-1.049 (0.486)**
<i>Income</i>	0.001 (0.000)*	0.003 (0.002)*	0.002 (0.001)*	0.007 (0.003)**	0.001 (0.000)*	0.002 (0.001)**	0.003 (0.001)**
<i>Unemployment</i>	0.004 (0.001)***	0.009 (0.002)***	0.007 (0.002)***	0.019 (0.004)***	0.002 (0.000)***	0.005 (0.001)***	0.007 (0.002)***
<i>Union</i>	-0.001 (0.000)***	-0.002 (0.001)***	-0.002 (0.000)***	-0.005 (0.001)***	-0.001 (0.000)***	-0.001 (0.000)***	-0.002 (0.000)***
<i>Constant</i>	1.468 (0.585)**	4.089 (1.435)**	2.094 (0.881)**	5.007 (2.341)**	0.805 (0.329)**	1.507 (0.633)**	2.094 (0.925)**
<i>Time/Region Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	850	850	850	850	850	850	850
1st Stage F-stat.	25.32	25.32	25.32	25.32	25.32	25.32	25.32
F(2,821) P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J-stat.	0.857	0.240	0.992	0.574	0.738	0.532	0.135
$\chi^2(1)$ P-value	0.354	0.625	0.319	0.449	0.390	0.466	0.713

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7. Poverty and Corruption : IV Estimation
Dependent Variable: Poverty

		<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	<i>I_ε=0.5</i>	<i>I_ε=1</i>	<i>I_ε=1.5</i>
<i>Corruption</i>	0.119 (0.019)***	0.055 (0.014)***	0.092 (0.018)***	0.052 (0.014)***	0.067 (0.015)***	0.059 (0.015)***	0.058 (0.015)***	0.069 (0.029)***
<i>Inequality</i>		0.625 (0.044)***	0.127 (0.030)***	0.417 (0.028)***	0.132 (0.012)***	1.050 (0.078)***	0.553 (0.041)***	0.366 (0.029)***
<i>Education</i>	2.621 (2.166)	2.924 (1.343)**	2.973 (1.774)	2.727 (1.317)**	2.457 (1.452)	2.811 (1.351)**	2.589 (1.329)**	2.369 (1.436)
<i>Education</i> ²	-33.287 (18.619)*	-29.659 (11.912)***	-32.420 (15.377)**	-27.789 (11.704)***	-28.498 (12.653)**	-29.369 (11.867)***	-27.906 (11.642)***	-27.052 (12.449)**
<i>Income</i>	-0.076 (0.009)***	-0.071 (0.004)***	-0.072 (0.007)***	-0.071 (0.004)***	-0.074 (0.006)***	-0.071 (0.005)***	-0.073 (0.005)***	-0.075 (0.005)***
<i>Unemployment</i>	0.006 (0.001)***	0.004 (0.001)***	0.005 (0.001)***	0.004 (0.001)***	0.005 (0.001)***	0.005 (0.001)***	0.004 (0.001)***	0.005 (0.001)***
<i>Constant</i>	0.167 (0.075)**	-0.033 (0.045)	0.076 (0.063)**	-0.016 (0.044)	0.123 (0.049)***	0.079 (0.045)	0.085 (0.044)	0.099 (0.049)**
<i>Time/RegionDummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	850	850	850	850	850	850	850	850
1st Stage F-stat.	25.329	17.770	22.350	17.270	19.780	18.830	18.410	19.410
F(2,823) P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hansen J-stat.	3.524	3.373	4.224	2.754	3.989	3.641	3.878	4.947
χ²(1) P-value	0.061	0.067	0.039	0.097	0.046	0.056	0.049	0.026

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 8. Inequality and Corruption: Spatial Autoregressive Estimation
Dependent Variables: Gini, SDL, RMD, CV, Atkinson Indices

	<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	$I_{\epsilon=0.5}$	$I_{\epsilon=1}$	$I_{\epsilon=1.5}$
<i>Corruption</i>	0.011 (0.002)***	0.019 (0.006)***	0.017 (0.003)***	0.047 (0.011)***	0.006 (0.001)***	0.012 (0.003)***	0.019 (0.004)***
<i>EITCB</i>	-2.293 (1.058)**	-6.989 (3.155)**	-3.156 (1.588)**	-9.629 (4.978)*	-1.479 (0.624)**	-2.789 (1.232)**	-3.914 (2.035)*
<i>EITCP</i>	2.269 (1.059)**	6.912 (3.156)**	3.122 (1.589)**	9.535 (4.979)*	1.466 (0.624)**	2.765 (1.233)**	3.874 (2.035)*
<i>AFDC/TANF</i>	-0.049 (0.010)***	-0.165 (0.038)***	-0.072 (0.016)***	-0.118 (0.043)***	-0.027 (0.006)***	-0.047 (0.011)***	-0.054 (0.017)***
<i>Education</i>	-0.669 (0.185)***	-2.555 (0.558)***	-0.990 (0.286)***	-1.435 (0.849)*	-0.342 (0.108)***	-0.557 (0.213)***	-0.729 (0.335)**
<i>Income</i>	0.002 (0.000)***	0.004 (0.001)***	0.003 (0.001)***	0.009 (0.002)***	0.001 (0.000)***	0.002 (0.000)***	0.004 (0.001)***
<i>Unemployment</i>	0.006 (0.001)***	0.012 (0.001)***	0.009 (0.001)***	0.025 (0.002)***	0.003 (0.000)***	0.007 (0.001)***	0.010 (0.001)***
<i>Union</i>	-0.001 (0.000)***	-0.002 (0.000)***	-0.002 (0.000)***	-0.005 (0.001)***	-0.001 (0.000)***	-0.001 (0.000)***	-0.002 (0.000)***
<i>Constant</i>	1.888 (0.449)***	3.552 (1.334)***	1.638 (0.675)**	4.312 (2.115)**	0.679 (0.265)***	1.281 (0.524)**	1.815 (0.865)**
<i>Time/Region Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	850	850	850	850	850	850	850
Wald Test of ρ							
$\chi^2(1)$	45.994	6.510	48.761	20.839	41.538	37.645	22.873
P-value	0.000	0.011	0.000	0.000	0.000	0.000	0.000
LM Test of ρ							
$\chi^2(1)$	38.780	5.919	40.962	18.504	34.760	31.461	19.496
P-value	0.000	0.015	0.000	0.000	0.000	0.000	0.000
Log Likelihood	2140.739	1123.972	1778.999	872.062	2600.365	2040.098	1672.099

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 9. Inequality and Corruption: Spatial Autoregressive Model
 (Corruption instrumented by ethnic and religious fractionalization indices for 1970 and 1971)
Dependent Variables: *Gini, SDL, RMD, CV, Atkinson Indices*

	<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	$I_{\epsilon}=0.5$	$I_{\epsilon}=1$	$I_{\epsilon}=1.5$
<i>Corruption</i>	0.095 (0.011)***	0.212 (0.029)***	0.149 (0.016)***	0.395 (0.048)***	0.053 (0.006)***	0.106 (0.012)***	0.154 (0.019)***
<i>EITCB</i>	-2.691 (1.061)**	-7.978 (3.127)**	-3.809 (1.601)**	-11.074 (5.099)**	-1.698 (0.628)***	-3.202 (1.254)**	-4.463 (2.099)**
<i>EITCP</i>	2.684 (1.062)**	7.939 (3.129)**	3.801 (1.603)**	11.051 (5.100)**	1.694 (0.628)***	3.196 (1.254)**	4.452 (2.099)**
<i>AFDC/TANF</i>	-0.058 (0.011)***	-0.182 (0.038)***	-0.087 (0.016)***	-0.152 (0.044)***	-0.032 (0.006)***	-0.057 (0.012)***	-0.068 (0.017)***
<i>Education</i>	-0.829 (0.181)***	-2.879 (0.546)***	-1.250 (0.278)***	-2.034 (0.846)**	-0.431 (0.106)***	-0.731 (0.210)***	-0.967 (0.333)***
<i>Income</i>	0.001 (0.000)***	0.003 (0.001)***	0.002 (0.001)***	0.007 (0.002)***	0.001 (0.000)***	0.002 (0.000)***	0.003 (0.001)***
<i>Unemployment</i>	0.004 (0.001)***	0.009 (0.001)***	0.007 (0.001)***	0.018 (0.002)***	0.002 (0.000)***	0.004 (0.001)***	0.007 (0.001)***
<i>Union</i>	-0.001 (0.000)***	-0.002 (0.000)***	-0.001 (0.000)***	-0.005 (0.001)***	-0.001 (0.000)***	-0.001 (0.000)***	-0.002 (0.000)***
<i>Constant</i>	1.409 (0.452)***	4.044 (1.325)***	1.994 (0.681)***	5.033 (2.166)**	0.790 (0.267)***	1.492 (0.532)***	2.099 (0.892)**
<i>Time/Region Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	850	850	850	850	850	850	850
<i>Wald Test of ρ</i>							
$\chi^2(1)$	12.605	1.282	12.429	4.122	11.565	9.219	4.475
<i>P-value</i>	0.000	0.258	0.000	0.042	0.001	0.002	0.034
<i>LM Test of ρ</i>							
$\chi^2(1)$	11.159	0.988	11.117	3.785	10.031	8.053	3.978
<i>P-value</i>	0.001	0.320	0.001	0.052	0.002	0.005	0.046
<i>Log Likelihood</i>	2169.892	1139.838	1809.594	897.389	2627.865	2068.465	1696.615

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 10. Poverty and Corruption: Spatial Autoregressive Estimation
Dependent Variable: Poverty

		<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	$I_{\epsilon=0.5}$	$I_{\epsilon=1}$	$I_{\epsilon=1.5}$
<i>Corruption</i>	0.016 (0.003)***	0.009 (0.002)***	0.014 (0.003)***	0.009 (0.002)***	0.010 (0.002)***	0.010 (0.002)***	0.009 (0.002)***	0.009 (0.002)***
<i>Inequality</i>		0.729 (0.036)***	0.145 (0.037)***	0.484 (0.023)***	0.156 (0.009)***	1.224 (0.068)***	0.647 (0.33)***	0.399 (0.022)***
<i>Education</i>	6.257 (1.299)***	3.933 (1.090)***	5.521 (1.193)***	3.614 (1.092)***	3.894 (1.056)***	3.965 (1.057)***	3.662 (1.036)***	3.785 (1.038)***
<i>Education</i> ²	-64.836 (11.698)***	-37.469 (9.959)***	-54.041 (10.884)***	-34.549 (9.967)***	-40.456 (9.474)***	-38.537 (9.561)***	-36.432 (9.352)***	-38.637 (9.279)***
<i>Income</i>	-0.065 (0.004)***	-0.068 (0.003)***	-0.065 (0.003)***	-0.068 (0.003)***	-0.071 (0.003)***	-0.068 (0.003)***	-0.070 (0.003)***	-0.071 (0.003)***
<i>Unemployment</i>	0.007 (0.000)***	0.005 (0.000)***	0.006 (0.000)***	0.005 (0.000)***	0.005 (0.000)***	0.005 (0.000)***	0.005 (0.000)***	0.005 (0.000)***
<i>Constant</i>	0.023 (0.042)	-0.093 (0.034)***	-0.029 (0.039)	-0.069 (0.034)**	0.065 (0.034)*	0.031 (0.033)	0.038 (0.032)	0.036 (0.033)
<i>Time/Region Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	850	850	850	850	850	850	850	850
Wald Test of ρ								
$\chi^2(1)$	57.925	0.590	8.894	0.752	1.038	0.109	0.090	1.062
P-value	0.000	0.443	0.003	0.386	0.308	0.741	0.764	0.303
LM Test of ρ								
$\chi^2(1)$	46.375	0.591	12.807	0.752	0.979	0.109	0.089	0.989
P-value	0.000	0.442	0.000	0.386	0.322	0.742	0.765	0.320
Log Likelihood	1991.452	2197.588	2067.939	2205.517	2170.653	2186.210	2197.126	2172.677

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 11. Poverty and Corruption: Spatial Autoregressive Estimation
 (Corruption instrumented by ethnic and religious fractionalization indices for 1970 and 1971)
Dependent Variable: Poverty

		<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	$I_{\epsilon}=0.5$	$I_{\epsilon}=1$	$I_{\epsilon}=1.5$
<i>Corruption</i>	0.102 (0.012)***	0.043 (0.011)***	0.079 (0.013)***	0.040 (0.011)***	0.050 (0.011)***	0.047 (0.011)***	0.044 (0.011)***	0.050 (0.011)***
<i>Inequality</i>		0.712 (0.036)***	0.137 (0.036)***	0.474 (0.023)***	0.151 (0.009)***	1.192 (0.068)***	0.632 (0.033)***	0.389 (0.022)***
<i>Education</i>	4.825 (1.304)***	3.443 (1.083)***	4.479 (1.168)***	3.178 (1.088)***	3.295 (1.053)***	3.423 (1.053)***	3.163 (1.035)***	3.185 (1.035)***
<i>Education</i> ²	-53.027 (11.751)***	-33.649 (9.869)***	-45.727 (10.648)***	-31.171 (9.904)***	-35.631 (9.424)***	-34.294 (9.512)***	-32.505 (9.312)***	-33.871 (9.229)***
<i>Income</i>	0.071 (0.004)***	-0.070 (0.003)***	-0.069 (0.004)***	-0.070 (0.003)***	-0.073 (0.003)***	-0.071 (0.003)***	-0.072 (0.003)***	-0.074 (0.003)***
<i>Unemployment</i>	0.006 (0.001)***	0.004 (0.000)***	0.005 (0.000)***	0.004 (0.000)***	0.005 (0.000)***	0.004 (0.000)***	0.004 (0.000)***	0.005 (0.000)***
<i>Constant</i>	0.083 (0.042)**	-0.067 (0.034)*	0.019 (0.040)	-0.046 (0.035)	0.092 (0.034)***	0.058 (0.033)*	0.062 (0.033)*	0.065 (0.033)
<i>Time/Region Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Observations</i>	850	850	850	850	850	850	850	850
Wald Test of ρ								
$\chi^2(1)$	22.713	2.952	2.475	3.029	0.065	1.950	1.747	0.068
P-value	0.000	0.086	0.116	0.082	0.798	0.163	0.186	0.794
LM Test of ρ								
$\chi^2(1)$	18.214	3.059	2.955	3.133	0.064	1.994	1.785	0.066
P-value	0.000	0.080	0.086	0.077	0.801	0.158	0.182	0.797
Log Likelihood	2008.143	2197.784	2076.478	2204.985	2173.162	2187.063	2197.962	2175.531

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 12. Inequality and Corruption : OLS Estimation (No Outliers)
Dependent Variables: Gini, SDL, RMD, CV, Atkinson Indices

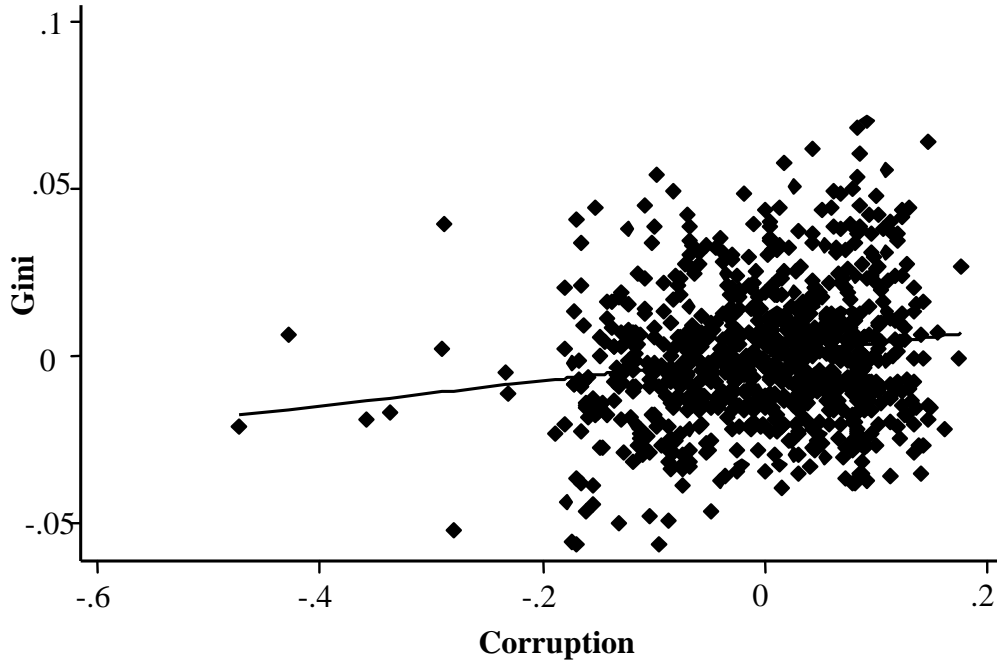
	<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	<i>I_{ε=0.5}</i>	<i>I_{ε=1}</i>	<i>I_{ε=1.5}</i>
<i>Corruption</i>	0.016 (0.003)***	0.033 (0.008)***	0.025 (0.005)***	0.068 (0.016)***	0.009 (0.002)***	0.018 (0.004)***	0.027 (0.006)***
<i>EITCB</i>	-2.223 (1.133)**	-7.809 (3.088)**	-3.111 (1.701)*	-9.082 (5.129)*	-1.428 (0.661)**	-2.653 (1.293)**	-3.675 (2.109)*
<i>EITCP</i>	2.196 (1.133)*	7.729 (3.089)**	3.070 (1.703)*	8.981 (5.131)*	1.412 (0.662)**	2.625 (1.294)**	3.633 (2.109)*
<i>AFDC/TANF</i>	-0.053 (0.011)***	-0.136 (0.029)***	-0.077 (0.017)***	-0.128 (0.046)***	-0.029 (0.006)***	-0.051 (0.012)***	-0.059 (0.018)***
<i>Education</i>	-0.783 (0.185)***	-2.545 (0.489)***	-1.179 (0.285)***	-1.833 (0.860)**	-0.408 (0.108)***	-0.679 (0.214)***	-0.895 (0.338)***
<i>Income</i>	0.002 (0.000)***	0.003 (0.001)***	0.003 (0.001)***	0.009 (0.002)***	0.001 (0.000)***	0.002 (0.000)***	0.004 (0.001)***
<i>Unemployment</i>	0.006 (0.001)***	0.013 (0.001)***	0.010 (0.001)***	0.026 (0.002)***	0.004 (0.000)***	0.007 (0.001)***	0.010 (0.001)***
<i>Union</i>	-0.001 (0.000)***	-0.003 (0.000)***	-0.002 (0.000)***	-0.006 (0.001)***	-0.001 (0.000)***	-0.001 (0.000)***	-0.002 (0.000)***
<i>Constant</i>	1.249 (0.482)***	3.975 (1.313)***	1.749 (0.724)**	4.207 (2.181)*	0.683 (0.281)**	1.273 (0.549)**	1.780 (0.897)**
<i>Time/Region Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	837	837	837	836	837	837	836
Adj. R-squared	0.62	0.71	0.61	0.48	0.62	0.58	0.52

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

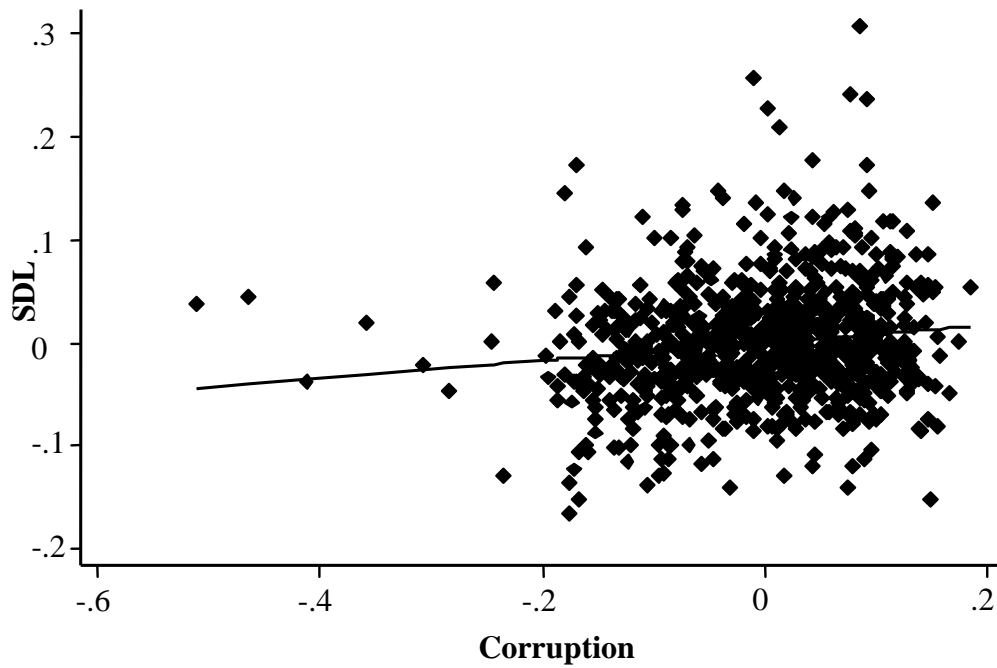
Table 13. Poverty and Corruption: OLS Estimation (Outliers Excluded)
Dependent Variable: Poverty

		<i>Gini</i>	<i>SDL</i>	<i>RMD</i>	<i>CV</i>	$I_{\epsilon=0.5}$	$I_{\epsilon=1}$	$I_{\epsilon=1.5}$
<i>Corruption</i>	0.024 (0.004)***	0.012 (0.003)***	0.019 (0.004)***	0.011 (0.003)***	0.013 (0.003)***	0.013 (0.003)***	0.012 (0.003)***	0.012 (0.003)***
<i>Inequality</i>		0.714 (0.033)***	0.154 (0.037)***	0.473 (0.022)***	0.158 (0.009)***	1.209 (0.064)***	0.642 (0.031)***	0.406 (0.021)***
<i>Education</i>	5.817 (1.327)***	4.130 (1.097)***	5.318 (1.188)***	3.827 (1.096)***	4.010 (1.056)***	4.139 (1.058)***	3.866 (1.037)***	3.901 (1.038)***
<i>Education</i> ²	-60.811 (11.809)***	-39.094 (9.997)***	-51.746 (10.747)***	-36.329 (9.988)***	-40.924 (9.481)***	-39.850 (9.560)***	-37.913 (9.344)***	-39.141 (9.279)***
<i>Income</i>	-0.068 (0.004)***	-0.068 (0.003)***	-0.066 (0.004)***	-0.067 (0.003)***	-0.069 (0.003)***	-0.067 (0.004)***	-0.068 (0.003)***	-0.069 (0.003)***
<i>Unemployment</i>	0.008 (0.001)***	0.005 (0.000)***	0.007 (0.001)***	0.005 (0.000)***	0.005 (0.000)***	0.005 (0.000)***	0.005 (0.000)***	0.005 (0.000)***
<i>Constant</i>	0.062 (0.043)	-0.101 (0.034)***	-0.018 (0.041)	-0.078 (0.034)**	0.058 (0.033)*	0.022 (0.032)	0.027 (0.032)	0.029 (0.033)
<i>Time/Region Dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	837	837	837	837	837	837	837	837
R-squared	0.67	0.81	0.74	0.81	0.80	0.80	0.81	0.80

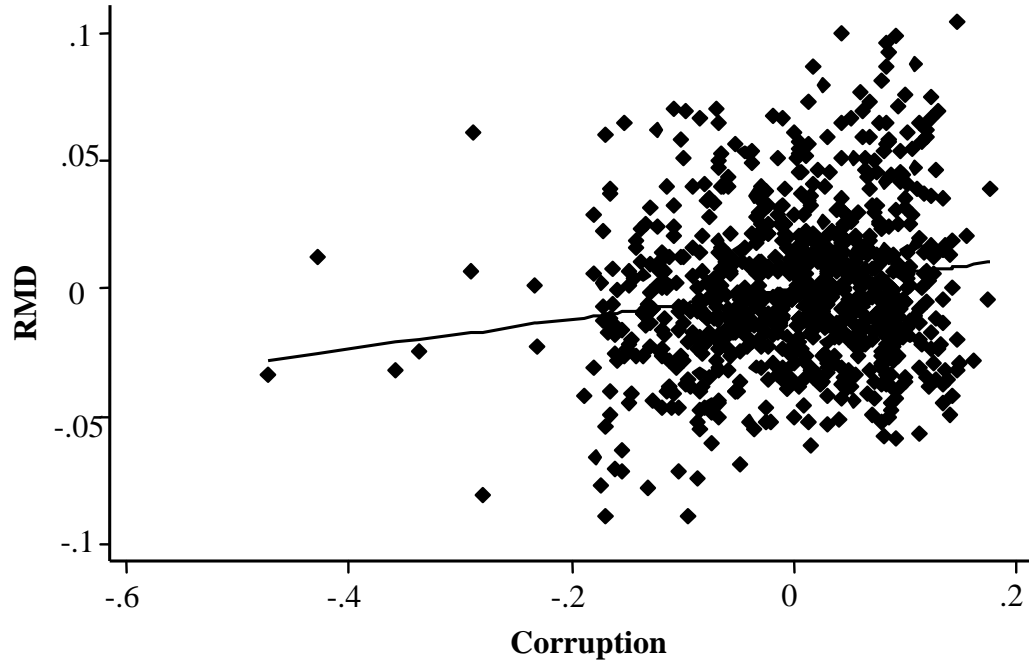
Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%



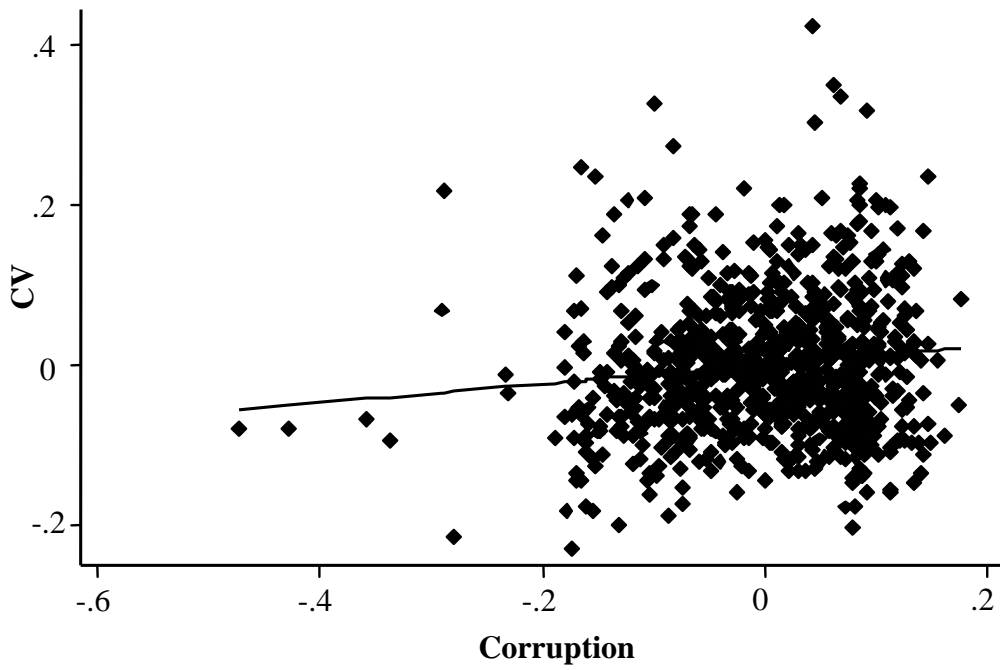
**Figure 1. Partial Regression Plot
Gini and Corruption**



**Figure 2. Partial Regression Plot
SDL and Corruption**



**Figure 3. Partial Regression Plot
RMD and Corruption**



**Figure 4. Partial Regression Plot
CV and Corruption**

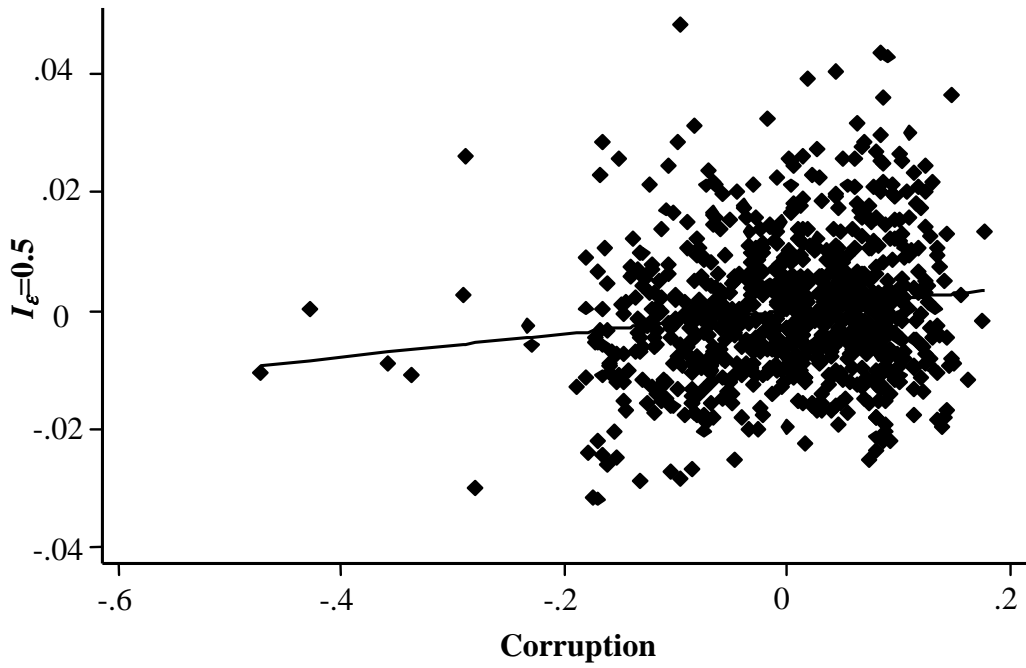


Figure 5. Partial Regression Plot
 $I_{\epsilon=0.5}$ and Corruption

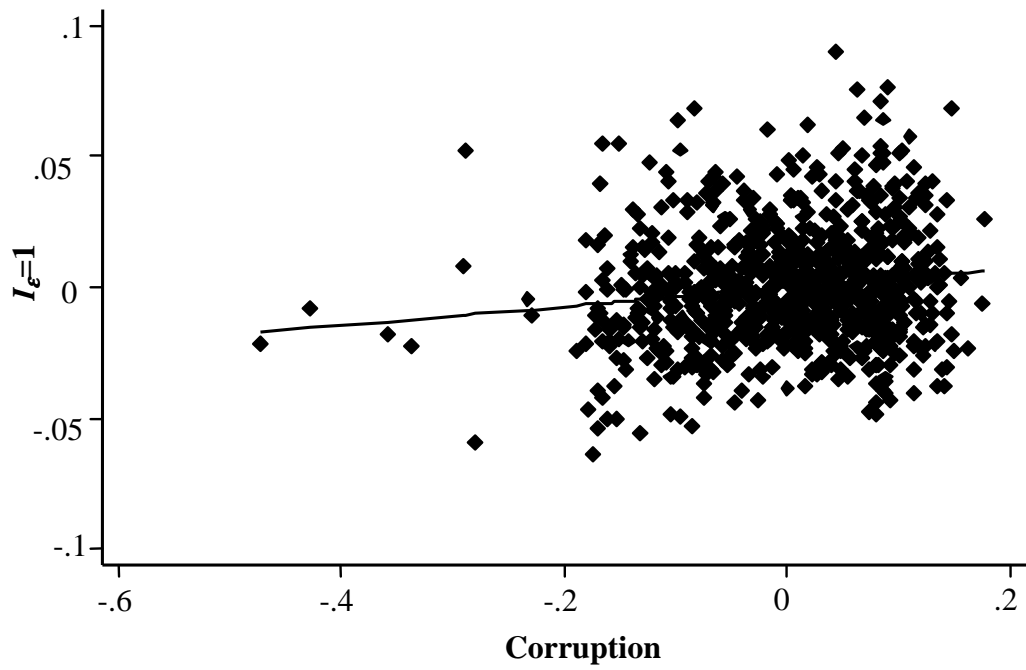


Figure 6. Partial Regression Plot
 $I_{\epsilon=1}$ and Corruption

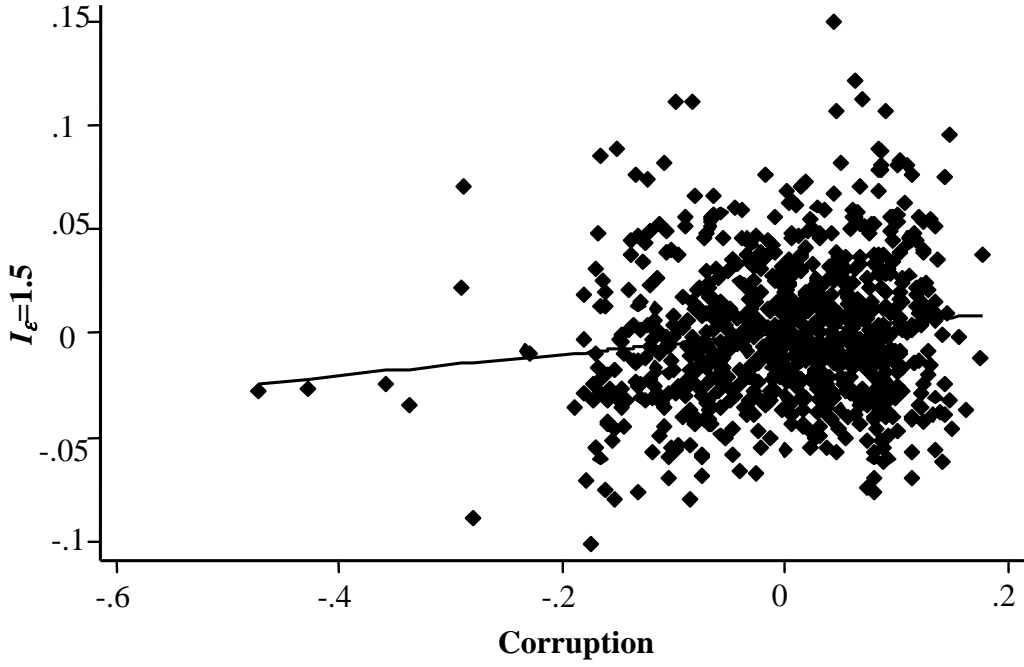


Figure 7. Partial Regression Plot
 $I_{\xi=1.5}$ and Corruption

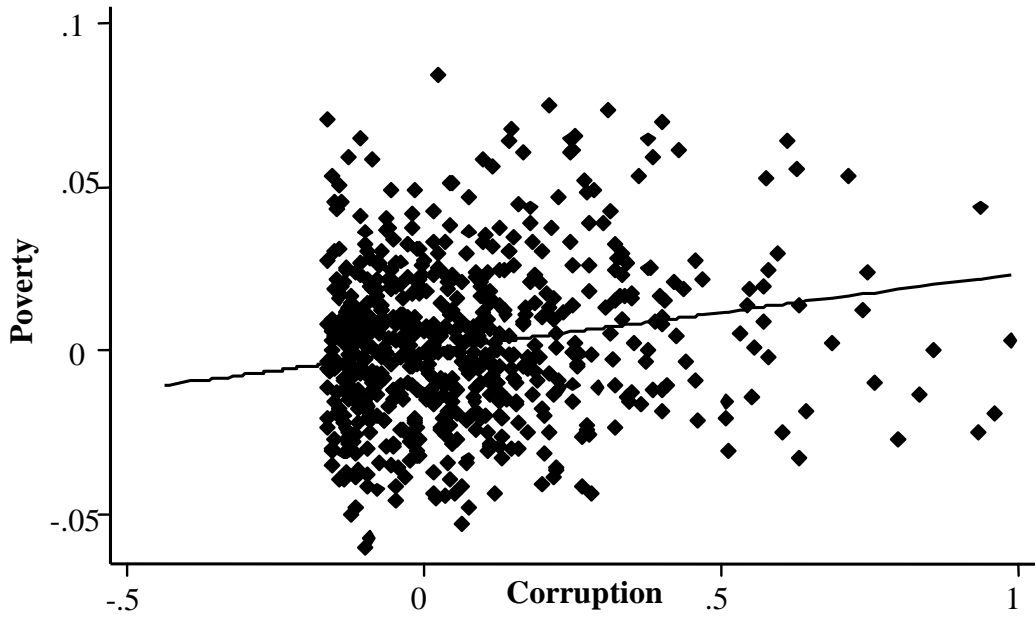


Figure 8. Partial Regression Plot
Poverty and Corruption

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