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The relationship between corruption and income inequality in U.S. states: evidence from a panel cointegration and error correction model

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Abstract We investigate the causality between corruption and income inequality within a multivariate framework using a panel data set of all 50 U.S. states over the period 1980 to 2004. The heterogeneous panel cointegration test by Pedroni (Oxf. Bull. Econ. Stat. 61:653–670, 1999; Econom. Theory 20:597–627, 2004) indicates that in the long run corruption and the unemployment rate have a positive and statistically significant impact on income inequality while a negative impact is found for real personal income per capita, education, and unionization rate. The Granger-causality results associated with a panel vector error correction model indicate both short-run and long-run bidirectional causality between corruption and income inequality.

Keywords Corruption · Income inequality · Panel unit root and cointegration tests · Granger-causality

1 Introduction

The relationship between corruption and income inequality has been a subject of investigation by a number of researchers in recent years.[1] Is there a causal relationship between

[1]Recent empirical studies include Li et al. (2000), Chong and Calderon (2000), Gupta et al. (2002), Chong and Gradstein (2007), and Dincer and Gunalp (2008).

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corruption and income inequality? If there is, what is the direction of causality? Some researchers argue that an increase in corruption causes greater income inequality. The burden of corruption falls disproportionately on low income individuals who pay a larger proportion of their incomes in the form of bribes than high income individuals.[2] Others argue that corruption distorts indirectly the redistributive role of government by diverting government resources away from programs (i.e., education and health services) that benefit mostly low income individuals. On the other hand, it is very likely that greater income inequality causes an increase in corruption as well. Income inequality provides the basis for corruption in that high income individuals relative to low income individuals have more opportunities and resources to engage in bribery. As income inequality increases, the number of low income individuals who are deprived of services provided by the government, such as education and health, increases. In turn, these individuals become easy targets of bribery.

Given the prevailing debate on the relationship between corruption and income inequality, we extend the recent cross-country study by Chong and Gradstein (2007) on the causal relationship between corruption and income inequality by employing a unique panel dataset for all 50 U.S. states over the period 1980 to 2004. Using data from U.S. states is quite advantageous for a variety of reasons. First, it minimizes the problems associated with data comparability often encountered in cross-country studies related to corruption. Data, particularly on income inequality as well as on corruption for U.S. states, are more comparable than those for different countries. Second, and perhaps more importantly, it allows us to use a more objective measure of corruption (the number of government officials convicted in a state for crimes related to corruption) instead of subjective cross-country corruption indices assembled by various investment risk services.

Section 2 provides a brief overview of the empirical literature analyzing the relationship between corruption and income inequality. Section 3 describes the data and methodology along with the empirical results. Concluding remarks are given in Sect. 4.

2 Brief overview of the empirical literature

While it is widely recognized that the fight against corruption is necessary for economic growth, there are only a few empirical studies that focus on the relationship between corruption and income inequality. Gupta et al. (2002), among others, argue that the benefits from corruption are likely to accrue to the better connected individuals within the high income groups of the society. According to Johnston (1989), corruption favors the 'haves' rather than the 'have nots' particularly if the stakes are large. Tanzi (1998) suggests that corruption distorts the redistributive role of government in that only the better connected individuals get the most profitable government projects; therefore, it is less likely that the government is able to improve the distribution of income and make the economic system more equitable.

Using data from a mixed group of countries (i.e., low, middle, and high-income), Li et al. (2000) and Chong and Calderon (2000) find an inverse U-shaped relationship between corruption and income inequality. Both studies find a positive relationship in high-income countries and a negative relationship in low-income countries. On the other hand, Gupta et al. (2002), using a smaller sample of countries, find a positive and linear relationship between corruption and income inequality. In a more recent study, Dincer and Gunalp (2008),

[2] For example, a corruption survey conducted by World Bank in the case of Cambodia reveals that lower income individuals on average spend 2.3% of their income on bribes compared to 0.9% for higher income individuals.

using data from U.S. states, also find a positive and linear relationship between corruption and income inequality which confirms the cross-country findings of Gupta et al. (2002).[3]

Although these studies present persuasive evidence regarding the effects of corruption on income inequality, none of them addresses the issue of causality in the Granger-sense between corruption and income inequality. The underlying assumption in these studies is that the direction of causality is from corruption to income inequality. However, as alluded to earlier, it is very likely that the direction of causality is from income inequality to corruption. Uslaner (2006) argues that income inequality provides the basis for corruption, which in turn, leads to greater income inequality. According to You and Khagram (2005), the individuals who belong to high income groups have more opportunities and resources to engage in corruption. The individuals who belong to low and middle income groups are unable to combat the spread of corruption, no matter how motivated they are, due to the lack of resources. As income inequality increases, a greater number of low income individuals become susceptible to bribery in order to secure access to various government services.

More recently, Chong and Gradstein (2007) address the issue of causality between corruption and income inequality. They employ a panel dataset of more than 100 countries based on five (ten) year averages across eight (four) time periods between 1960 and 2000 to estimate a panel vector autoregressive model. Their results support the presence of bidirectional causality between corruption and income inequality. We extend the work of Chong and Gradstein (2007) by examining the causal relationship between corruption and income inequality within a multivariate framework using a panel dataset of all 50 U.S. states.

3 Data, methodology, and results

We use annual data from 1980 to 2004 for all 50 U.S. states. Corruption is measured by the number of government officials convicted in a state for crimes related to corruption in a specific year. The data are obtained from the Justice Department's "Report to Congress on the Activities and Operations of the Public Integrity Section" and cover a broad range of crimes from election fraud to wire fraud.[4] In response to Watergate and to growing concerns about corruption, in 1976 a Public Integrity Section was established in the Justice Department to prosecute corrupt public officials. The Public Integrity Section reports the number of public officials convicted for the crimes related to corruption annually (Maxwell and Winters 2004). Following Glaeser and Saks (2006), to reduce heteroskedasticity, we deflate the number of convictions by state population. The corruption data are based on federal public corruption convictions. In other words, the corruption cases tried by state and local prosecutors are not included in the data. It is also possible to question how corruption among public officials such as U.S. House and Senate members affect income inequality in the state they represent. Nevertheless, in our opinion, federal convictions at least provide the evidence of the existence of a "culture of corruption" in a state. We believe the number of convictions is a good measure of corruption in a state for two reasons. First, as Meier and Holbrook (1992) argue, it does not only have face validity, it also has construct validity. States such as Louisiana, Illinois, and New York rank high on corruption, while states such as Vermont,

[3] In addition to the papers regarding corruption and income inequality, there is also a significant number of papers on rent seeking and income inequality such as Shughart II et al. (2003).

[4] This state convictions data have been used to measure corruption in several studies such as Goel and Rich (1989), Fisman and Gatti (2002), Fredriksson et al. (2003), Glaeser and Saks (2006), Dincer (2008), and Dincer and Gunalp (2008).

Oregon, and Utah rank low. All of the empirical studies using the same measure of corruption find results which are supported by theory. Second, it is not related to prosecutorial resources in a state (Meier and Holbrook 1992: 137). Since the data are from convictions resulting from federal prosecutions, state resources are not consequential. Income inequality is measured by the Gini index for each state obtained from the U.S. Census Bureau calculated using the U.S. Current Population Survey (CPS) data which are based on pretax household incomes.

Although corruption is not endemic in the United States as it is in several other countries, it does exist. According to the Justice Department, in the last two decades more than 20,000 public officials and private individuals were convicted for crimes related to corruption and more than 5000 are awaiting trial. It is possible to find examples of corruption supporting the theoretical arguments presented earlier in Sect. 2. The Governor of the State of Illinois, Rod Blagojevich, is a perfect example of how corruption affects the redistributive role of the government (Tanzi 1998). Rod Blagojevich was indicted on 19 counts of corruption in the beginning of 2009. Two of the allegations in the indictment are particularly interesting. According to the indictment, the Governor delayed state aid to a publicly supported school and a publicly supported hospital to extort campaign contributions. As another example, the Democratic and Republican political machines of Chicago and New York support the argument presented by You and Khagram (2005). During 1960s and 1970s, city workers in Chicago and New York were required to kick back a certain percentage of their salaries to the political machines to secure their jobs. Today, political machines are not run by either party but, they still exist and they are run by mayors (Kweit and Kweit 1998). Is it possible to combat the spread of corruption if income inequality is high? Not if the justice system is corrupt as well. In the United States, the justice system, on the whole, is not corrupt. On the other hand, it is possible to find individual cases of corruption.[5]

There is, in fact, a relatively large variation in the number of convictions across the U.S. states. Based on the averages across the 25 years covered in our dataset, Mississippi and Oregon are the most and least corrupt states, respectively. The South is the most corrupt region with an average of 0.35 corruption convictions per 100,000 people. Three of the five most corrupt states are in the South: Mississippi, Louisiana, and Tennessee. The least corrupt region is the West with an average of 0.24 corruption convictions per 100,000 people. Two of the five least corrupt states are in the West: Oregon and Washington. When we look at the inequality data we see a pattern similar to that of corruption. The South has the highest inequality with an average Gini index of 0.43. Four of the five states with the highest inequality are in the South: Louisiana, Mississippi, Texas, and Alabama. The West, again, has the lowest income inequality with an average Gini index of 0.41. Two of the five states with the lowest inequality are in the West: Utah and Wyoming.

In addition to the corruption and income inequality variables, we include a set of state economic and demographic control variables in our analysis to minimize omitted variable bias (Lütkepohl 1982). The state economic variables consist of real per capita personal income and the unemployment rate. The income data are from the Bureau of Economic Analysis (BEA) and the unemployment data are from the Bureau of Labor Statistics (BLS). The demographic variables include education and unionization rate for each state. Education is

[5] During the 1980s, in Chicago, for example, nearly 100 people, including judges, lawyers, police officers, and politicians, were indicted for fixing cases ranging from misdemeanors to felonies (*Chicago Tribune*, August 5, 1983). Corruption in the justice system even affects election outcomes. For example, at the beginning of 2009, five public officials in Kentucky, including a judge, were indicted for buying votes (*Boston Globe*, April 13, 2009).

Table 1 Summary statistics: U.S. states, 1980–2004

Variable	Mean	Std. Dev.	Min.	Max.
GINI	0.42	0.03	0.34	0.52
COR	0.29	0.29	0.00	2.55
UR	0.06	0.02	0.02	0.17
Y	14,096	2,647	8,503	24,259
EDUC	0.81	0.28	0.79	1.00
UNION	0.16	0.07	0.03	0.38

Variable definitions and sources:
GINI: Gini index of income inequality, http://www.census.gov/hhes/www/income/histinc/state/statetoc.html
COR: Number of government officials convicted in a state for crimes related to corruption per 100,000 people, http://www.usdoj.gov/criminal/pin
UR: Unemployment rate, http://www.bls.gov/lau/data.htm
Y: Real personal income per capita (Base period: 1982–1984=100), http://www.bea.gov/regional/spi
EDUC: Share of elementary and secondary school enrollment in the population between 5 to 17 years old education, http://nces.ed.gov/programs/digest
UNION: Unionization rate, http://www.unionstats.com

measured as the share of elementary and secondary school enrollment in the population of 5 to 17 year old persons obtained from the National Center for Education Statistics. The unionization rate is measured by the estimates provided by Barry Hirsch and David Macpherson from the Union Membership and Coverage Database. The summary statistics are presented in Table 1.

Our empirical analysis begins by first testing for panel unit roots and cointegration followed by the estimation of a panel vector error correction model in order to perform Granger-causality tests.

3.1 Panel unit root tests

Consider the following autoregressive specification:

$$y_{it} = \rho_i y_{it-1} + \delta_i X_{it} + \varepsilon_{it} \tag{1}$$

where $i = 1, \dots, N$ for each state in the panel; $t = 1, \dots, T$ refers to the time period; X_{it}represents the exogenous variables in the model including fixed effects or individual time trend; ρ_i are the autoregressive coefficients; and ε_{it} are the stationary error terms. If $\rho_i < 1$, y_{it} is considered to be weakly trend stationary; on the other hand, if $\rho_i = 1$, then y_{it} contains a unit root.[6]

In light of parameter heterogeneity and the need to avoid potential biases introduced due to an improper specification, Im et al.'s (2003) panel unit root test is utilized which allows for heterogeneous autoregressive coefficients.[7] Specifically, Im et al. (2003) suggest averaging

[6] There are several panel unit root tests. The Breitung (2000) and Levin et al. (2002) panel unit root tests assume a homogeneous autoregressive unit root under the alternative hypothesis. Im et al. (2003) allows for a heterogeneous autoregressive unit root under the alternative hypothesis. Maddala and Wu (1999) and Choi (2001) use the non-parametric Fisher statistic in testing for unit roots. Hadri (2000) and Carrioni-Silvestre et al. (2005) examine the null hypothesis of stationarity.

[7] The Breitung (2000), Hadri (2000), Choi (2001), Levin et al. (2002), and Carrioni-Silvestre et al. (2005) tests were also undertaken. All tests indicated that the respective variables contain a unit root. Results are available upon request from the authors.

Table 2 IPS panel unit root tests with trend: U.S. states, 1980–2004

Variables	IPS
GINI	−0.79(3)
Δ*GINI*	−4.47(2)[a]
COR	−0.66(4)
Δ*COR*	−5.21(2)[a]
UR	−0.84(2)
Δ*UR*	−5.12(1)[a]
Y	−0.87(3)
Δ*Y*	−6.04(1)[a]
EDUC	−0.92(3)
Δ*EDUC*	−4.24(2)[a]
UNION	−0.90(3)
Δ*UNION*	−5.13(2)[a]

Notes: Δ represents the first-difference operator. Critical value at the 1% significance level denoted by "a" is -2.45 with trend. Numbers in parentheses are the augmented lags included in the unit root test

the augmented Dickey-Fuller (ADF) unit root tests while allowing for different orders of serial correlation in (1) as follows:

$$y_{it} = \rho_i y_{it-1} + \sum_{j=1}^{p_i} \varphi_{ij} \varepsilon_{it-j} + \delta_i X_{it} + u_{it} \tag{2}$$

where p_i represents the number of lags in the ADF regression. The null hypothesis is that each series in the panel contains a unit root ($H_0 : \rho_i = 1\ \forall_i$). The alternative hypothesis is that at least one of the individual series in the panel is stationary ($H_0 : \rho_i < 1$). Im et al. (2003) specify a *t-bar* statistic as the average of the individual ADF statistics as follows:

$$t\text{-}bar = \frac{1}{N} \sum_{i=1}^{N} t_{\rho_i} \tag{3}$$

where t_{ρ_i} is the individual t-statistic for testing $H_0 : \rho_i = 1\ \forall_i$ from (2). The *t-bar* statistic is normally distributed under the null hypothesis with the critical values for given values of N and T provided by Im et al. (2003). The IPS panel unit root tests, presented in Table 2, indicate that all variables are integrated of order one.

3.2 Panel cointegration tests

The heterogeneous panel cointegration test advanced by Pedroni (1999, 2004) which allows for cross-section interdependence with different individual effects is specified as follows:

$$GINI_{it} = \alpha_i + \delta_i t + \gamma_{1i} COR_{it} + \gamma_{2i} UR_{it} + \gamma_{3i} Y_{it} + \gamma_{4i} EDUC_{it} + \gamma_{5i} UNION_{it} + \varepsilon_{it} \tag{4}$$

where $i = 1, \dots, N$ for each state in the panel and $t = 1, \dots, T$ refers to the time period. The parameters α_i and δ_i allow for the possibility of state-specific fixed effects and deterministic trends, respectively; ε_{it} denotes the estimated residuals which represent deviations from the long-run relationship. To test the null hypothesis of no cointegration, $\rho_i = 1$, the following unit root test on the residuals is performed:

$$\varepsilon_{it} = \rho_i \varepsilon_{it-1} + w_{it} \tag{5}$$

Table 3 Panel cointegration tests: U.S. states, 1980–2004

Within dimension test statistics		Between dimension test statistics	
Panel v-statistic	37.33483[a]	Group ρ-statistic	−9.39778[a]
Panel ρ-statistic	−8.61239[a]	Group PP-statistic	−2.18402[a]
Panel PP-statistic	−3.19448[a]	Group ADF-statistic	−2.82224[a]
Panel ADF-statistic	−3.15262[a]		

Notes: Of the seven tests, the panel v-statistic is a one-sided test whereby large positive values reject the null hypothesis of no cointegration whereas large negative values for the remaining test statistics reject the null hypothesis of no cointegration (see Pedroni 1999, for details on the heterogeneous panel and group mean panel cointegration statistics). Critical value at the 1% significance level denoted by "a": Panel v 31.738, panel ρ −25.130, panel PP −22.119, panel ADF −3.545, group ρ −28.849, group PP −22.119, group ADF −3.737

Pedroni (1999, 2004) proposes two sets of tests for cointegration: panel (within dimension) and group (between dimension) tests. The panel tests are based on the within dimension approach which include four statistics: panel v, panel ρ, panel PP, and panel ADF. These statistics essentially pool the autoregressive coefficients across different states for the unit root tests on the estimated residuals taking into account common time factors and heterogeneity across states. The group tests are based on the between dimension approach which include three statistics: group ρ, group PP, and group ADF. These statistics are based on averages of the individual autoregressive coefficients associated with the unit root tests of the residuals for each state in the panel. The panel and group tests both are distributed asymptotically as standard normal. Table 3 presents both the within and between dimension panel cointegration test statistics. All seven test statistics reject the null hypothesis of no cointegration at the 1% significance level.

Following Pedroni (2000), the long-run cointegrating relationship is estimated using the fully modified OLS (FMOLS) for heterogeneous cointegrated panels.[8] Table 4 reports the FMOLS results which reveal that all coefficients have the correct signs and are statistically significant at the 1% level. We find a positive relationship between corruption and income inequality confirming the findings of Gupta et al. (2002), Chong and Gradstein (2007), and Dincer and Gunalp (2008). According to our results, inequality is negatively related to per capita income, education, and unionization rate and positively related to the unemployment rate (Li et al. 2000; Chong and Calderon 2000; Glaeser 2005; Dincer and Gunalp 2008).

In order to infer the Granger-causal relationship between corruption and income inequality, a panel vector error correction model is specified (Pesaran et al. 1999). The Engle and Granger (1987) two-step procedure is performed by first estimating the long-run model specified in (4) in order to obtain the estimated residuals. Defining the lagged residuals from (4) as the error correction term, a six-equation dynamic error correction model is estimated. Equation (6) displays the equation for income inequality only for brevity where comparable equations for each of the right-hand side variables in (6) with the same general specification

[8]Although Kao and Chiang (1999) have suggested dynamic OLS (DOLS) for estimating the cointegrated panel vector, Phillips and Moon (1999) have shown that the FMOLS procedure corrects for endogeneity and serial correlation to the OLS estimator more efficiently, whereas the DOLS procedure suffers from not using the correct or optimal number of leads and lags for the explanatory variables as additional regressors.

Table 4 Panel FMOLS long-run estimates: U.S. states, 1980–2004

FMOLS estimates:

$$GINI = \underset{(3.14)^{a}}{0.296} + \underset{(6.45)^{a}}{0.043} COR + \underset{(8.62)^{a}}{0.417} UR - \underset{(-4.73)^{a}}{0.059} Y - \underset{(-5.20)^{a}}{0.624} EDUC - \underset{(-3.29)^{a}}{0.019} UNION$$

Diagnostics:

Adj. $R^2 = 0.73$	LM = 2.36	RESET = 2.11	HE = 1.97
	[0.18]	[0.23]	[0.32]

Notes: t-statistics are reported in parentheses and probability values in brackets. LM is the Lagrange multiplier test for serial correlation. RESET is the misspecification test. HE is White's heteroskedasticity test. Significance at the 1% level denoted by "a"

comprise the six-equation dynamic error correction model.

$$\Delta GINI_{it} = \alpha_{1j} + \sum_{k=1}^{q} \theta_{11ik} \Delta GINI_{it-k} + \sum_{k=1}^{q} \theta_{12ik} \Delta COR_{it-k} + \sum_{k=1}^{q} \theta_{13ik} \Delta UR_{it-k} + \sum_{k=1}^{q} \theta_{14ik} \Delta Y_{it-k} + \sum_{k=1}^{q} \theta_{15ik} \Delta EDUC_{it-k} + \sum_{k=1}^{q} \theta_{16ik} \Delta UNION_{it-k} + \lambda_{1i} \varepsilon_{it-1} + u_{1it} \tag{6}$$

where Δ is the first-difference operator; q is the lag length set at one based on likelihood ratio tests; and u is the serially uncorrelated error term. Short-run causality for each variable is determined by the statistical significance of the lagged coefficients using a partial F-test. Long-run causality in each equation is examined by the significance of the t-statistic for the coefficient on the respective error correction terms.

Given our focus on the causal relationship between income inequality and corruption, Table 5 presents the results of the short-run and long-run Granger-causality tests with respect to the income inequality and corruption equations. The estimated coefficients for each variable in the income inequality equation are jointly significant. Corruption has a positive and significant impact in the short-run on income inequality. The estimated coefficients for each of the control variables (real per capita income, education, and unionization rate) have a negative and significant short-run impact on income inequality whereas the unemployment rate has a positive and significant impact. Regarding the error correction term, it is statistically significant at the 1% level with an estimated speed of adjustment toward long-run equilibrium of 0.208 (roughly five years to adjust toward equilibrium). The estimated coefficients for each variable in the corruption equation, with the exception of the unionization rate, are jointly significant. Income inequality has a positive and significant impact in the short-run on corruption. The estimated coefficients for each of the control variables (real per capita income and education) have a negative and significant short-run impact on corruption whereas the unemployment rate has a positive and significant impact. However, the unionization rate is insignificant. The error correction term is again statistically significant at the 1% level with an estimated speed of adjustment toward long run equilibrium of 0.222, comparable to the results for the income inequality equation. The presence of bidirectional Granger-causality between corruption and income inequality lends support for the cross-country findings of Chong and Gradstein (2007).

Table 5 Panel causality test results: U.S. states, 1980–2004

Dependent variable	Sources of causation (independent variables)						
	Short-run						Long-run
	$\Delta GINI$	ΔCOR	ΔUR	ΔY	$\Delta EDUC$	$\Delta UNION$	ECT
(6a) $\Delta GINI$	–	10.56 (0.036)	11.65 (0.075)	12.92 (−0.038)	3.96 (−0.012)	5.91 (−0.097)	−0.208
		[0.00][a]	[0.00][a]	[0.00][a]	[0.04][b]	[0.02][b]	[0.00][a]
(6b) ΔCOR	10.68 (0.825)	–	12.26 (0.018)	10.64 (−0.017)	18.65 (−0.018)	2.37 (−0.078)	−0.222
	[0.00][a]		[0.00][a]	[0.00][a]	[0.00][a]	[0.12]	[0.00][a]

Notes: Partial F-statistics reported with respect to short-run changes in the independent variables. The sum of the lagged coefficients for the respective short-run changes is denoted in parentheses. ECT represents the coefficient of the error correction term. Probability values are in brackets. Significance at the 1 and 5% levels are denoted by "a" and "b", respectively

4 Concluding remarks

This study extends the recent cross-country study by Chong and Gradstein (2007) by utilizing panel data for all 50 U.S. states over the period 1980 to 2004 to infer the causal relationship between corruption and income inequality within a multivariate framework.[9] Pedroni's (1999, 2004) heterogeneous panel cointegration test reveals that there is a long-run equilibrium relationship not only between income inequality and corruption but also between income inequality and real per capita income, education, unemployment, and unionization. This long-run relationship suggests that corruption and unemployment have a positive and statistically significant impact on income inequality while real per capita income, education, and unionization have a negative and statistically significant impact. The estimation of a panel vector error correction model indicates the presence of both short-run and long-run bidirectional Granger-causality between corruption and income inequality. These results for U.S. states confirm the cross-country findings by Chong and Gradstein (2007).

These findings have significant policy implications. Considering the negative impact of an increase in per capita income on both income inequality and corruption in the long run, and the bidirectional causality between income inequality and corruption, economic growth appears to be the best policy not only to reduce income inequality but also to reduce corruption. There are, of course, many questions that arise from our analysis and a number of avenues for future research. For example, according to Ravallion (1997), income inequality plays a vital role in poverty reduction. He finds that poverty decreases significantly in countries that combine higher economic growth and lower income inequality. It is then quite likely that corruption affects poverty both directly and indirectly through income inequality and vice versa. Introducing poverty into the causal relationship between corruption and income inequality may help us better understand the relationship between poverty and income inequality.

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