

**CORRUPTION, INCOME INEQUALITY AND GROWTH:
EVIDENCE FROM U.S. STATES**

By

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Abstract: In this paper we analyze the effects of corruption on income inequality and growth. The analysis advances the existing literature in three 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 avoid comparing different countries by examining the differences in income inequality, growth, and corruption across U.S. states. Data on corruption as well as on income inequality and growth in U.S. states are more comparable than those for different countries, and U.S. states are more similar in other dimensions which are difficult to measure. Third, we employ 4-year and 5-year panels of income inequality and growth to control for unobserved state characteristics. We find robust evidence that increase in corruption (1) increases the Gini Coefficient of income inequality, and (2) decreases the income growth.

Keywords: Corruption, Income Inequality, Growth

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1. Introduction

Corruption keeps continuing to attract a great deal of attention as increasing number of empirical studies (e.g. Mauro 1995, Knack and Keefer 1995, Knack 1996, Keefer and Knack 1997, Hall and Jones 1999, Mo 2001, Pellegrini and Gerlagh 2004) present persuasive evidence regarding its detrimental effects on various economic variables such as income growth. All of the empirical studies find that corruption decreases income growth significantly. Most of the theoretical studies analyzing the effects of corruption explain its detrimental effects on growth by focusing on the weakness of the central government (Shleifer and Vishny 1993, Barreto 2000). According to Shleifer and Vishny (1993), for example, a weak central government allows independent governmental agencies impose independent bribes on the sale of complementary government goods such as permits. As the number of these agencies increases the total bribe rises to infinity and permit sales falls to zero, reducing investment and growth. Huntington (1968) argues that political modernization, a transition from an autocratic to a more democratic government, weakens the power of the central government and increases corruption by the changes it produces on the output side of the political system. “Modernization, particularly among later modernizing countries, involves the expansion of governmental authority and the multiplication of the activities subjected to governmental regulation (Huntington 1968, 61)”. Such an expansion of a weaker central government leads the emergence of independent government agencies taking bribes. The typical example of this phenomenon is post-Communist Russia. “To invest in a Russian company, a foreigner must bribe every agency involved in foreign investment including the foreign investment office, the relevant industrial ministry, the finance ministry, the executive branch of the local government, the legislative branch, the central bank, the state property bureau, and so on (Shleifer and Vishny 1993, 615)”. According to Shleifer and Vishny (1993), the second reason why corruption reduces growth is the secrecy inherent in corruption. Keeping corruption secret “shifts a country’s investments away from the highest value projects, such as health and education, into potentially useless

projects, such as defense and infrastructure, if the latter offer better opportunities for secret corruption (Shleifer and Vishny 1993, 616)".

Corruption does not only affect income growth but also affects the distribution of income. "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)". As Tanzi (1995) 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. Nevertheless, there are only a couple of empirical studies (Li et. al. 2000, Gupta et. al. 2002) analyzing the effects of corruption on income distribution whereas theoretical studies are almost non-existent. Both of the empirical studies find that corruption increases income inequality significantly.

In this study, we analyze the effects of corruption on income inequality and growth by using data from U.S. states. Our analysis advances the existing literature in three ways. First, we avoid comparing different countries by examining differences in income inequality, growth, and corruption across U.S. states. Data on corruption as well as on income inequality and growth 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. Second, 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 the crimes related to corruption. Finally, we employ 4-year and 5-year panels of income inequality and growth to control for unobserved state characteristics. We find robust evidence that increase in corruption increases income inequality and decreases income growth.

2. Data

As our measure of corruption across states we use data from the Justice Department's "Report to Congress on the Activities and Operations of the Public Integrity Section. The report gives the number of government officials convicted in a state for the crimes related to corruption. As Glaeser and Saks (2004) argue, using the number of convictions creates a problem since smaller number of government

officials is likely to be convicted in corrupt states. Following Glaeser and Saks (2004), to mitigate this problem, we focus on federal convictions. Since there are lags between time of crime and time of conviction, we use 4-year averages in inequality regressions for the period 1982-1997 and 5-year averages in growth regressions from 1986-2001. Following Glaeser and Saks (2004) we deflate the data on conviction by state population.

We measure income inequality across states by using data on Gini Coefficients given by Wu, Golan, and Perloff (2002). To measure income growth across states we use data on real chained dollar Gross State Product (GSP) given by Bureau of Economic Analysis. We also include a number of control variables to minimize the omitted variable bias. In income inequality regressions we include controls for education, unemployment, per capita GSP, and minimum wage along with dummy variables for each of the four census regions. Our measure of education is based on the data on the share of secondary school enrollment in population given by National Center for Education Statistics. Our unemployment data are given by Bureau of Labor Statistics. We use 4-year period averages for all control variables except the minimum wage. For minimum wage we use beginning of period data given by Neumark and Nizalova (2003). In growth regressions we include controls for initial GSP, education, investment, and population growth along with dummy variables for each of the four census regions. Our measure of investment is based on the data on the share of manufacturing employment in overall employment given by Bureau of Labor Statistics. Population data are given by Census Bureau. Except the initial GSP, we use 5-year period averages for all control variables.

3. Results

Corruption and Income Inequality

Our basic specification in inequality regressions is as follows:

$$Gini_{st} = \beta_0 + \beta_1 Corruption_{st} + \beta_2 X_{st} + \varepsilon_{st}$$

where $Gini_{st}$ represents the Gini Coefficient 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 (*Education, Unemployment, Per Capita GSP,*

Minimum Wage, and regional dummy variables *South*, *West*, and *Midwest*). Between 1982 and 1997, five most corrupt states appear to be Illinois, Alaska, Tennessee, Mississippi, and South Dakota whereas the five least corrupt states appear to be Vermont, Oregon, Washington, Utah, and New Hampshire. Regarding income inequality, Wisconsin, Vermont, Utah, Iowa, and Maine have the lowest Gini Coefficients (lowest income inequality) whereas California, New Mexico, Mississippi, Louisiana, and Texas have the highest Gini Coefficients (highest income inequality). The summary statistics for four 4-year periods between 1982 and 1997 and for fifty states of all variables are given in Table 1.

The results of Pooled Ordinary Least Squares (OLS) Estimation for six different specifications are given in Table 2. In all six specifications the estimated coefficient of $Corruption_{st}$ is positive and highly significant indicating that corruption increases income inequality. The first column gives Pooled OLS Estimation results of the specification without any control variables. In that specification, the estimated coefficient of $Corruption_{st}$ is equal to 0.039 indicating that an increase in the number of convictions for the crimes related to corruption by 1 (per 100.000 people) is associated with almost 4 percentage point increase in the Gini Coefficient. The other columns give the results of the specifications with the control variables. The estimated coefficient of $Corruption_{st}$ does not change drastically when we add the control variables. It is equal to 0.031 in the specification with all of the control variables and 0.041 in the specification with all of the control variables except the regional dummies.

The results of the Random Effects (RE) Estimation for six different specifications are given in Table 3. In most of the specifications the estimated coefficient of $Corruption_{st}$ is positive and highly significant indicating that corruption increases income inequality. It is equal to 0.011 in the specification without any control variables. Similar to the Pooled OLS Estimation, the estimated coefficient of $Corruption_{st}$ does not change drastically when we add the control variables. On the other hand, it loses its significance in the specification with all control variables.

Corruption and Growth

Our basic specification in growth regressions is as follows:

$$GSP\ Growth_{st} = \beta_0 + \beta_1 \ln Initial\ GSP_{st} + \beta_2 Corruption_{st} + \beta_3 \ln X_{st} + \varepsilon_{st}$$

where $GSP\ Growth_{st}$ represents the growth rate of real per capita GSP in state s during period t and $\ln Initial\ GSP_{st}$ represents the natural log of initial real per capita GSP. $Corruption_{st}$ again represents corruption whereas X_{st} represents the set of control variables that affect growth (*Education, Investment, Population Growth*, and regional dummy variables *South, West, and Midwest*). Between 1986 and 2000 five most corrupt states appear to be Illinois, North Dakota, South Dakota, Louisiana, and Mississippi whereas the five least corrupt states appear to be Oregon, New Hampshire, Utah, Nebraska, and Vermont. Regarding growth, Oregon, Idaho, New Mexico, South Dakota, and New Hampshire appear to have the highest growth whereas Alaska, Hawaii, Nevada, Louisiana, and Florida appear to have the lowest growth. The summary statistics for three 5-year periods between 1986 and 2000 and for fifty states of all variables are given in Table 4.

The results of Pooled Ordinary Least Squares (OLS) Estimation for five different specifications are given in Table 5. In all five specifications the estimated coefficient of $Corruption_{st}$ is negative and highly significant indicating that corruption decreases growth. The estimated coefficient is almost the same in all specifications. In the specification with all of the control variables it is equal to -0.012 indicating that an increase in the number of convictions for the crimes related to corruption by 1 (per 100.000 people) is associated with almost 1.2 percentage point decrease in growth.

Table 6 gives the results of RE Estimation for five specifications. In all five specifications the estimated coefficient of $Corruption_{st}$ is again negative and highly significant. RE Estimation gives only slightly different coefficient estimates. In the specification with all of the control variables except the regional dummies, for example, the estimated coefficient of $Corruption_{st}$ is equal to -0.011, whereas it is equal to -0.014 in Pooled OLS Estimation.

4. Robustness of the Results

The main robustness issue is whether the results are due to endogeneity. As Mauro (1995) argues high income growth is likely to lead to less corruption and high income inequality is likely to lead to more corruption. The 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 $Corruption_{st}$. Previous studies (Mauro 1995) use instruments such as ethnic fractionalization. Nevertheless, validity of ethnic fractionalization as an instrument is open to discussion. Based on Ellis and Dincer (2005), in this study, we use a new instrument: corruption in the neighboring states. Ellis and Dincer (2005) present a theoretical model predicting that corruption in the states which are close to each other tends to be close. For 48 states they provide supportive empirical evidence. They find that corruption in a state increases as corruption in the neighboring states increases. Table 7 gives the results of the Pooled IV Estimation regarding the effects of corruption on income inequality. Although the estimated coefficient of $Corruption_{st}$ is bigger it remains positive and highly significant in the specification with all of the control variables except region dummies. Estimated coefficient of $Corruption_{st}$ loses its significance when we use corruption in neighboring states as an instrument in random effects estimation. On the other hand when we use a more conservative instrument, lagged corruption, the estimated coefficient remains positive and highly significant in all specifications. The results of Random Effects IV Estimation regarding the effects of corruption on income inequality are given in Table 8.

The results of Pooled IV Estimation regarding the effects of corruption on growth are given in Table 9. The estimated coefficient of $Corruption_{st}$ is smaller but it remains negative and highly significant in most of the specifications. Again, the estimated coefficient of $Corruption_{st}$ loses its significance when we use corruption in neighboring states as an instrument in random effects estimation. On the other hand, when we use lagged corruption as an instrument, the estimated coefficient of $Corruption_{st}$ remains negative and highly significant in all specifications.

5. Conclusion

In this study we analyze the effects of corruption on income inequality and growth by using data from U.S. states. We find that increase in corruption increases income inequality and decreases growth. Our results are robust to different specifications. An increase in the number of convictions for the crimes related to corruption by 1 (per 100.000 people) is associated with almost 4 percentage point increase in the Gini Coefficient and 1.2 percentage point decrease in growth.

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Table 1. Summary Statistics Inequality

	Mean	Standard Deviation	Minimum	Maximum
<i>Gini</i>	0.337	0.029	0.285	0.420
<i>Corruption</i>	0.315	0.210	0	1.183
<i>Education</i>	0.050	0.005	0.037	0.075
<i>Unemployment</i>	0.064	0.019	0.026	0.149
<i>Per Capita GSP (100²)</i>	2.532	0.604	1.609	7.144
<i>Minimum Wage</i>	3.732	0.427	3.350	5.250

Table 2. Pooled OLS Inequality

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Gini</i>	<i>Gini</i>	<i>Gini</i>	<i>Gini</i>	<i>Gini</i>	<i>Gini</i>
<i>Corruption</i>	0.039	0.039	0.036	0.043	0.041	0.031
	(0.010)***	(0.009)***	(0.009)***	(0.010)***	(0.009)***	(0.008)***
<i>Education</i>		-0.616			-0.682	-0.625
		(0.305)**			(0.281)**	(0.302)**
<i>Unemployment</i>			0.231		0.462	0.289
			(0.091)**		(0.091)***	(0.076)***
<i>Minimum Wage</i>				0.025	0.034	0.030
				(0.005)***	(0.005)***	(0.004)***
<i>Per Capita GSP</i>					-0.007	-0.003
					(0.003)***	(0.003)
<i>South</i>						0.036
						(0.005)***
<i>Midwest</i>						0.003
						(0.004)
<i>West</i>						0.017
						(0.006)***
<i>Constant</i>	0.325	0.356	0.311	0.230	0.222	0.220
	(0.004)***	(0.016)***	(0.007)***	(0.018)***	(0.023)***	(0.021)***
Observations	200	200	200	200	200	200
R-squared	0.08	0.09	0.10	0.21	0.31	0.54

Robust standard errors in parentheses

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

Table 3. Random Effects Inequality

	(1)	(2)	(3)	(4)	(5)	(6)
	Gini	Gini	Gini	Gini	Gini	Gini
<i>Corruption</i>	0.011	0.012	0.009	0.011	0.007	0.007
	(0.005)**	(0.005)**	(0.005)*	(0.005)**	(0.005)	(0.005)
<i>Education</i>		-0.634			-0.432	-0.475
		(0.309)**			(0.298)	(0.293)
<i>Unemployment</i>			0.466		0.481	0.443
			(0.074)***		(0.076)***	(0.074)***
<i>Minimum Wage</i>				0.007	-0.003	-0.002
				(0.007)	(0.007)	(0.007)
<i>Per Capita GSP</i>					0.005	0.005
					(0.003)	(0.003)*
<i>South</i>						0.037
						(0.007)***
<i>Midwest</i>						0.004
						(0.008)
<i>West</i>						0.015
						(0.008)**
<i>Constant</i>	0.325	0.359	0.288	0.302	0.308	0.293
	(0.004)***	(0.017)***	(0.007)***	(0.025)***	(0.030)***	(0.030)***
Observations	200	200	200	200	200	200

Standard errors in parentheses

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

Table 4. Summary Statistics Growth

	Mean	Standard Deviation	Minimum	Maximum
<i>GSP Growth</i>	0.021	0.010	-0.019	0.046
<i>Initial GSP (100²)</i>	2.555	0.534	1.576	4.406
<i>Corruption</i>	0.324	0.199	0	0.976
<i>Education</i>	0.049	0.006	0.038	0.074
<i>Investment</i>	0.127	0.049	0.027	0.234
<i>Population Growth</i>	0.011	0.010	-0.015	0.056

Table 5. Pooled OLS Growth

	(1)	(2)	(3)	(4)	(5)
	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>
<i>ln Initial GSP</i>	-0.013	-0.011	-0.009	-0.009	-0.012
	(0.005)**	(0.005)**	(0.006)	(0.006)	(0.007)*
<i>Corruption</i>	-0.015	-0.014	-0.013	-0.014	-0.012
	(0.005)***	(0.005)***	(0.005)***	(0.005)***	(0.005)**
<i>ln Investment</i>		0.003	0.003	0.003	0.002
		(0.002)	(0.003)	(0.003)	(0.003)
<i>ln Education</i>			0.008	0.008	0.012
			(0.009)	(0.009)	(0.011)
<i>ln Population Growth</i>				-0.001	0.004
				(0.007)	(0.009)
<i>South</i>					-0.005
					(0.003)*
<i>Midwest</i>					-0.002
					(0.003)
<i>West</i>					-0.005
					(0.005)
<i>Constant</i>	0.162	0.147	0.153	0.147	0.200
	(0.053)***	(0.049)***	(0.049)***	(0.058)**	(0.074)***
Observations	150	150	150	150	150
R-squared	0.12	0.14	0.14	0.14	0.17

Robust standard errors in parentheses

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

Table 6. Random Effects Growth

	(1)	(2)	(3)	(4)	(5)
	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>
<i>ln Initial GSP</i>	-0.018	-0.016	-0.014	-0.014	-0.017
	(0.005)***	(0.005)***	(0.005)***	(0.005)**	(0.005)***
<i>Corruption</i>	-0.012	-0.011	-0.011	-0.011	-0.009
	(0.004)***	(0.004)**	(0.004)**	(0.005)**	(0.005)*
<i>ln Investment</i>		0.003	0.004	0.003	0.003
		(0.002)*	(0.002)*	(0.002)*	(0.002)
<i>ln Education</i>			0.007	0.007	0.007
			(0.008)	(0.008)	(0.009)
<i>ln Population Growth</i>				-0.003	0.001
				(0.006)	(0.007)
<i>South</i>					-0.006
					(0.003)**
<i>Midwest</i>					-0.002
					(0.003)
<i>West</i>					-0.003
					(0.004)
<i>Constant</i>	0.204	0.187	0.188	0.178	0.227
	(0.047)***	(0.046)***	(0.046)***	(0.051)***	(0.058)***
Observations	150	150	150	150	150
Number of state_code	50	50	50	50	50

Standard errors in parentheses

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

Table 7. Pooled IV Inequality

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Gini</i>	<i>Gini</i>	<i>Gini</i>	<i>Gini</i>	<i>Gini</i>	<i>Gini</i>
<i>Corruption</i>	0.132	0.130	0.133	0.280	0.199	0.272
	(0.094)	(0.093)	(0.091)	(0.166)*	(0.071)***	(0.350)
<i>Education</i>		-0.597			-0.683	-1.291
		(0.350)*			(0.481)	(1.309)
<i>Unemployment</i>			0.080		0.216	-0.060
			(0.199)		(0.197)	(0.545)
<i>Minimum Wage</i>				0.035	0.042	0.042
				(0.011)***	(0.008)***	(0.020)**
<i>Per Capita GSP</i>					-0.019	-0.029
					(0.009)**	(0.041)
<i>South</i>						0.010
						(0.040)
<i>Midwest</i>						-0.010
						(0.021)
<i>West</i>						0.029
						(0.023)
<i>Constant</i>	0.296	0.327	0.290	0.120	0.186	0.231
	(0.030)***	(0.035)***	(0.021)***	(0.084)	(0.048)***	(0.067)***
Observations	200	200	200	200	200	200

Robust standard errors in parentheses

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

Table 8. Random Effects IV Inequality

	(1)	(2)	(3)	(4)	(5)	(6)
	Gini	Gini	Gini	Gini	Gini	Gini
Corruption	0.090	0.088	0.073	0.090	0.067	0.050
	(0.031)***	(0.030)***	(0.022)***	(0.031)***	(0.023)***	(0.020)**
Education		-0.748			-0.850	-0.827
		(0.437)*			(0.417)**	(0.376)**
Unemployment			0.422		0.383	0.370
			(0.108)***		(0.106)***	(0.093)***
Minimum Wage				-0.004	-0.007	-0.005
				(0.011)	(0.009)	(0.008)
Per Capita GSP					-0.005	-0.002
					(0.005)	(0.005)
South						0.032
						(0.009)***
Midwest						0.002
						(0.009)
West						0.020
						(0.009)**
Constant	0.302	0.343	0.272	0.315	0.358	0.335
	(0.010)***	(0.024)***	(0.010)***	(0.036)***	(0.043)***	(0.039)***
Observations	200	200	200	200	200	200

Standard errors in parentheses

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

Table 9. Pooled IV Growth

	(1)	(2)	(3)	(4)	(5)
	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>
<i>ln Initial GSP</i>	-0.014	-0.013	-0.012	-0.012	-0.013
	(0.005)***	(0.006)**	(0.007)*	(0.007)	(0.007)*
<i>Corruption</i>	-0.025	-0.028	-0.027	-0.039	-0.036
	(0.015)*	(0.014)**	(0.014)*	(0.024)	(0.039)
<i>ln Investment</i>		0.002	0.002	0.001	-0.000
		(0.003)	(0.003)	(0.004)	(0.005)
<i>ln Education</i>			0.006	0.004	0.008
			(0.009)	(0.010)	(0.012)
<i>ln Population Growth</i>				-0.013	-0.008
				(0.013)	(0.021)
<i>South</i>					-0.002
					(0.005)
<i>Midwest</i>					-0.001
					(0.004)
<i>West</i>					-0.004
					(0.005)
<i>Constant</i>	0.174	0.169	0.172	0.130	0.164
	(0.056)***	(0.057)***	(0.056)***	(0.064)**	(0.095)*
Observations	150	150	150	150	150

Robust standard errors in parentheses

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

Table 10. Random Effects IV Growth

	(1)	(2)	(3)	(4)	(5)
	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>	<i>GSP Growth</i>
<i>ln Initial GSP</i>	-0.018	-0.016	-0.015	-0.014	-0.017
	(0.005)***	(0.005)***	(0.005)***	(0.005)***	(0.006)***
<i>Corruption</i>	-0.019	-0.018	-0.017	-0.020	-0.016
	(0.006)***	(0.006)***	(0.006)***	(0.007)***	(0.007)**
<i>ln Investment</i>		0.003	0.003	0.003	0.003
		(0.002)	(0.002)	(0.002)	(0.002)
<i>ln Education</i>			0.005	0.005	0.006
			(0.008)	(0.008)	(0.009)
<i>ln Population Growth</i>				-0.007	-0.002
				(0.006)	(0.007)
<i>South</i>					-0.005
					(0.003)*
<i>Midwest</i>					-0.002
					(0.003)
<i>West</i>					-0.003
					(0.004)
<i>Constant</i>	0.206	0.194	0.194	0.171	0.216
	(0.046)***	(0.047)***	(0.047)***	(0.052)***	(0.059)***
Observations	150	150	150	150	150

Standard errors in parentheses

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