Public Corruption and State Infrastructure: Opportunities and Impacts

by

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An honors thesis submitted in partial fulfillment

of the requirements for the degree of

Bachelor of Science

Undergraduate College

Leonard N. Stern School of Business

New York University

May 2018

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Abstract

This paper explores the opportunities for and impacts of public corruption through an evaluation of state infrastructure spending and quality. While the relationship between state corruption and infrastructure spending contains simultaneity bias, this study focuses largely on corruption as a function of construction spending. It finds that greater proportions of construction spending at the state level do create greater opportunities for corrupt activities amongst public officials. It also finds that public corruption convictions are a significant predictor of the locations of roads projects, as states with higher levels of corruption are more likely to siphon public funds for road improvements on lesser-used roads, such as rural and arterial roads, as opposed to urban roads or highways.

1 Introduction

1.1 Background Information

Most agree that public corruption has a negative impact on society, as it is often associated with an unequal redistribution of wealth from taxpayers to public officials and their cronies. Both theory and empirical studies[1] suggest that corrupt public agents favor investment projects which generate higher bribes over those that are efficient. As a result, corruption is often seen to diminish the impacts of public spending on social outcome goals while simultaneously distorting the quality of public services.

Economic studies conducted at the country level published by Ablo and Reinikka, Ehrlich and Lui and Mauro support these claims. Ablo and Reinikka found that between 1991 and 1995, only 30% of the allocated expenditures per primary school pupil in Ukraine ended up

[1] Rose-Ackerman, 1997.

actually reaching the schools[2], suggesting that corruption indeed increases state expenditures while simultaneously reducing output quantity[3]. Corruption also distorts spending structure, as Ehrlich and Lui found that educational expenditures as a share of GDP declined in countries with higher corruption[4], while Mauro found that military expenditures as a share of GDP increase in the wake of higher corruption[5].

The allocation inefficiencies arising from public corruption can also be explained through a more theoretical framework. If we think of all corrupt exchanges as an official awarding a bidder with some type of contract, it's fair to assume that corrupt officials <u>expect</u> a personal benefit proportional to the benefit that a bidder receives from being granted such a contract. As a result, we should expect corrupt officials to favor projects with higher rent potentials and greater oversight opacity. Given this framework, Lambsdorff concludes that corruption thus "motivates politicians and public servants to impose […] market restrictions so as to maximize the resulting rents and bribes paid in connection with them."[6] Other economists such as Susan Rose-Ackerman also conclude that given this motivation, the projects managed under corrupt officials are also likely to be more inefficient and wasteful[7].

Construction projects are a particularly prime area for corrupt activity. Charles Kenny attributes much of this result to market structure[8]. Most construction industries are dominated by a few, monopolistic, regional firms. This, in combination with the fact that most construction projects are closely tied to the government, creates both opportunities and incentives for firms to offer bribes to public officials in the hopes of winning government construction contracts.

[2] Ablo and Reinikka, 1998.
[3] Ibid.
[4] Ehrlich and Lui, 1999.
[5] Mauro, 1997.
[6] Lambsdorff, 2002.
[7] Rose-Ackerman, 1997.
[8] Kenny, 2007.

Construction is also more idiosyncratic in nature, making it difficult to compare and determine competitive, fair-market prices for certain projects.

Endogeneity between public corruption and construction spending complicate empirical tests that utilize the two variables. To fully understand the relationship between corruption and state infrastructure, I choose to isolate each direction by first reviewing several empirical studies that focus on corruption's impact on state budgeting, and then conducting two empirical tests. The first explores the other directional relationship between public corruption and infrastructure spending while the second explores corruption's impact on the qualitative aspects of infrastructure projects.

$$\text{Construction Spending} \longleftrightarrow \text{Corruption}$$

Diagram 1: Construction and Corruption Causal Diagram

1.2 Corruption's Impact on Construction & Other State Expenditures

While corruption and construction spending are two jointly determined variables, most research has been concerned with infrastructure spending and budgeting distortion as a function of corruption. The following three economic studies each utilize slightly different datasets and econometric methods to conclude that corruption has a significant impact on certain types of public sector expenditures.

$$\text{Construction Spending} \longleftarrow \text{Corruption}$$

Diagram 2: Corruption's Impact on Public Expenditures

Lui and Mikesell find that public corruption increases the overall spending per state and the level of construction spending[9]. Their analysis utilizes a general method of moments estimator[10], which identifies internal instruments to correct endogeneity on the corruption variable. This is due to the difficulty in finding external instruments for corruption which are valid and consistent for every state throughout a period of 20 years[11]. Lui and Mikesell's conclusion, that corruption tends to expand total budgets per state, is consistent with the bureaucracy model[12], which states that public officials want to maximize budgets to increase their personal benefits, which are tied to the salaries and the bribes they receive from public spending contracts.

Cordis also finds that public corruption has a distortionary effect on U.S. public expenditures[13]. Instead of using panel estimators, she conducts a cross-sectional analysis[14] by averaging all government spending per year by state, then implementing a two-stage least squares regression with external instruments. Cordis's main conclusion is that state-level public corruption decreases expenditures in sectors such as public welfare, health and education[15].

Delavallade finds that corruption's impacts on budgeting and expenditures also hold internationally[16]. Her data comes from 64 countries between the years 1996 and 2001, and her study uses a three-stage least squares[17] which first estimates endogenous variables, then estimates the variance-covariance matrix of the residuals, and finally uses that matrix to conduct

[9] Lui and Mikesell, 2014.
[10] Ibid.
[11] Lui and Mikesell, 2014.
[12] Ibid.
[13] Cordis, 2012.
[14] Ibid.
[15] Cordis, 2012.
[16] Delavallade, 2006.
[17] Ibid.

a general-least squares estimation. Her study finds that countries with higher levels of corruption spend less on health, education and social protection, and more on fuel and energy[18].

Conclusions from the three studies on corruption's distortionary impact on state budgeting and expenditures seem to be consistent with theoretical claims. We should naturally expect corrupt officials to spend less on sectors such as education, health and social welfare because these sectors provide the least amount of rents and thus the least opportunities for personal benefits to public officials. Increasing expenditures in areas such as construction and energy also seem consistent, as these industries are both more opaquely regulated and often rely on government contracts, thus generating large rent opportunities and incentives for firms and public officials.

1.3 Empirical Motivation

The rest of this paper differentiates itself from other studies in a few main ways. First, it uses a two-stage least squares regression to analyze the other causal relationship, corruption as a function of construction spending, which will allow us to determine if there are opportunities for corruption that arise from construction spending. It will then evaluate the relationship between corruption and the location of infrastructure projects through fixed effects regressions.

$$\text{Construction Spending} \longrightarrow \text{Corruption}$$

Diagram 3: Construction's Impact on Public Corruption

All further analysis in this paper is restricted to the United States. This eliminates cultural differences while standardizing the legal definition of public corruption.

[18] Ibid.

2 Data and Descriptive Analysis

All data utilized in this study is state-level data. Everything was collected from publicly available information published through various U.S. government agencies and assembled into a panel. Years range from 1998 – 2014, and observations include all U.S. states except for Hawaii[19].

2.1 Corruption Variables

This study captures state-level corruption by using data from the Department of Justice's Public Integrity Section. Commonly referred to as the DOJ's PIN dataset, it is compiled through reports submitted to Congress on the number of federal corruption convictions, aggregated together by state, and published annually online. While PIN data is the most widely used dataset in empirical studies involving U.S. state-level corruption, true corruption levels per state is one of the most difficult variables to accurately capture for several reasons.

First, conviction numbers are an imperfect measure of true crime levels—they are a non-linear byproduct of the intensity of the punishments or the intensity of policing. In this case, it is difficult to observe the true levels of corruption in conviction data because high levels of public corruption in the policing and justice systems might actually result in fewer arrests and convictions. When we plot the number of arrests against the unobservable, true number of corrupt public officials, we should expect the relationship to resemble an inverted parabola[20].

[19] Hawaii is excluded due to missing time series data on average temperature and total rainfall.
[20] White, 1988.

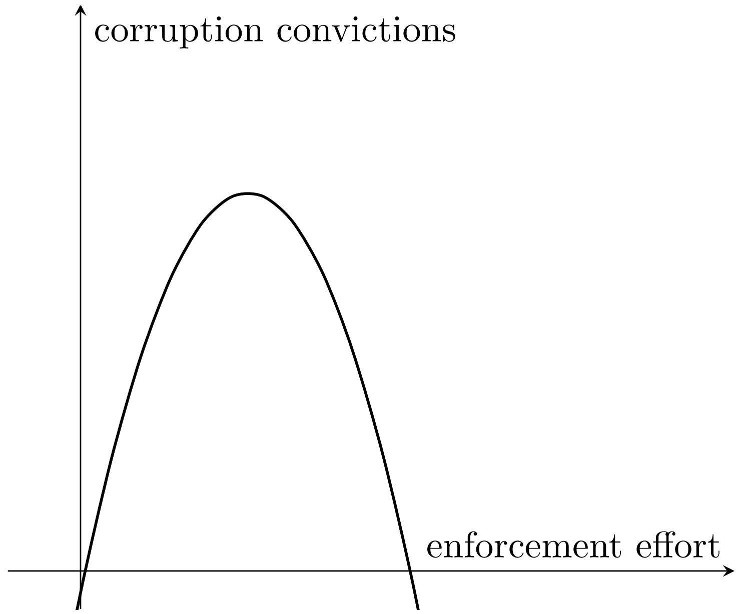


Diagram 4: True Public Corruption and Observed Convictions

While both intersections with the x-axis represent zero arrests, they are explained by different enforcement scenarios. The left-hand side of the parabola captures scenarios where fewer corruption arrests are explained by the lack of enforcement while the right-hand side represents fewer corruption arrests due to higher levels of enforcement, which discourages corruption. Further complications also arise if there is corruption within the enforcement units. Consequently, it is difficult to draw strict conclusions about the underlying corruption, or even chart enforcement effort, by just looking at convictions data.

The next area of contention is the choice of dataset itself. There are multiple datasets that aggregate the number of federal-corruption arrests per state, each with its own set of strengths and weaknesses. While the PIN dataset is the most commonly used in U.S. state-level corruption empirical studies, it remains largely criticized for being a dataset compiled through surveys from federal prosecutors, not actual administrative records[21]. Those favoring administrative records note that federal prosecutors are supposed to record instances of "official corruption" in item

[21] Cordis and Milyo, 2016.

codes when reporting arrests, hypothetically improving accuracy of the data. Unfortunately, the Federal Justice Statistics Resource Center stopped classifying public corruption cases after it changed parts of its reporting system in 2001, which again complicates even the ability to observe correct levels of corruption convictions.

Despite certain difficulties, the PIN data's main comparable dataset is assembled and published by a non-profit organization known as the Transnational Records Access Clearinghouse. The dataset, commonly referenced as TRAC data, is compiled through administrative records available through the Freedom of Information Act. Even though the TRAC data is based directly on administrative records, the changes in reporting methods still makes it difficult to accurately capture all corruption arrests per state.

Regardless, differences between results generated from PIN and TRAC data are likely not that significant. Cordis and Milyo's study[22] exploring the different types of data on corruption convictions found that the PIN and TRAC datasets are highly correlated. A different study by Cordis, which measured public expenditure structure as a function of corruption, also found that results did not depend on which corruption dataset she used[23].

To compare corruption levels across states, I divide total convictions per year by state population and multiply by 1 million to generate a measure of corruption levels per capita.

Table 1: Corruption Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Number of Convictions	833	19.253	22.492	0	166
Population per State	833	5,951,719	6,485,956	480,045	38,802,500
State Convictions per 1 Million	833	3.417	3.005	0.000	25.521

2.2 Revenue, Expenditures and Wages – State Spending Variables

[22] Cordis and Milyo, 2016.
[23] Cordis, 2012.

This study uses two types of state financial variables. The first captures actual infrastructure expenditure levels, while the second controls for inflation and relative budget size within each state.

State infrastructure expenditure variables come from the U.S. Census Bureau's State and Local Government Finance Data. The data is organized by Revenues and Expenditures, which are both stated in aggregate amounts per account and reported in thousands of dollars. Revenues include total taxes and intergovernmental revenues, and expenditures include total construction expenditures as well as construction expenditures per sector. This study normalizes construction expenditures per state by using the proportion of construction spending over total expenditures. Likewise, it uses revenue as a means of controlling for the size of state budgets, and divides total revenue by state population (in thousands). This effectively reports the amount of revenue per person, and allows us to compare relative budget sizes across all states.

To control for relative inflation levels per state, I introduce the average hourly wage per construction laborer, which comes from the Bureau of Labor and Statistics' Occupational Employment Statistics (OES). This variable does not factor in wages from construction managers as managerial wages might become inflated by public corruption.

Table 2: Highway and Construction Spending Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Avg. Hourly Wage of Construction Labor	782	14.507	3.542	8.270	24.820
Revenue/Population	833	5.866	2.405	1.529	24.082
Construction Spending/Expenditures	833	0.061	0.020	0.021	0.144
Highway Construction/Total Construction	833	0.646	0.136	0.207	0.938

2.3 Weather – Construction Instruments & Pavement Quality Controls

Weather data is used in both empirical tests, first as external instruments for construction spending, and then as controls for infrastructure wear and tear. Data includes the average annual temperatures per state in Fahrenheit and the total annual rainfall in inches, and comes from the Department of Commerce's National Oceanic and Atmospheric Administration's National Centers for Environmental Data. Time series data was collected by state from 1998 – 2014 and matched into the panel.

Table 3: Weather and Temperature Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Avg. Annual Temperature	833	52.288	8.403	24.000	72.500
Avg. Annual Rainfall in Inches	833	37.327	14.606	6.240	73.780

2.4 Bridge & Pavement Quality – Infrastructure Variables

State infrastructure data comes from the U.S. Department of Transportation's Federal Highway Administration Highway Statistic Series. This paper considers public infrastructure quality in two ways: defunct bridges and pavement roughness.

Defunct bridges are distinguished by those that are structurally deficient and those that are functionally obsolete. Structurally deficient bridges are those that are extremely poor condition and are no longer 100% safe to drive over, while functionally obsolete bridges are those that do not have adequate lane widths, shoulder widths or vertical clearances to serve the necessary traffic demands. Variables are normalized across states by dividing defunct bridges over total bridges per state. I also include a third variable which is a simple aggregation of structurally deficient and functionally obsolete bridges to measure total defunct bridges. While this may double count bridges which are classified as both structurally deficient and functionally obsolete, it may well be reasonable for states to receive a double penalty on bridges that are extremely poor quality.

Pavement quality comes from the FHA's Highway Statistic Series HM-64 Report, and uses the International Roughness Index (IRI) to classify quality. Pavements with an IRI value less than or equal to 95 inches per mile are considered *good* quality roads; pavements with an IRI value greater than or equal to 170 inches per mile are considered *poor* quality; pavements with an IRI value greater than or equal to 220 inches per mile are considered *terrible* quality. Pavement roughness is aggregated and then normalized into proportions by dividing the miles of rough pavement by the total miles of reported pavement.

Table 4: Infrastructure Quality Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Structurally Defunct Bridges	833	0.125	0.063	0.018	0.408
Functionally Obsolete Bridges	833	0.158	0.077	0.028	0.441
Total Poor Quality Pavement	782	0.097	0.076	0.0003	0.359
Poor Highway Pavement	782	0.038	0.047	0.000	0.413
Poor Arterial Pavement	782	0.124	0.098	0.0001	0.475
Poor Urban Pavement	782	0.185	0.109	0.001	0.508
Poor Rural Pavement	782	0.047	0.048	0.000	0.277
Poor Urban Highway Pavement	782	0.058	0.057	0.000	0.505
Poor Rural Highway Pavement	766	0.021	0.040	0.000	0.422
Poor Urban Arterial	782	0.243	0.140	0.001	0.690
Poor Rural Arterial	782	0.055	0.057	0.000	0.347
Total Terrible Quality Pavement	782	0.035	0.035	0.000	0.179
Terrible Highway Pavement	782	0.009	0.015	0.000	0.135
Terrible Arterial Pavement	782	0.047	0.047	0.000	0.233
Terrible Urban Pavement	782	0.076	0.058	0.000	0.285
Terrible Rural Pavement	782	0.012	0.016	0.000	0.122
Terrible Urban Arterial	782	0.105	0.079	0.000	0.420
Terrible Rural Arterial	782	0.014	0.020	0.000	0.208
Terrible Urban Highway	782	0.013	0.020	0.000	0.200
Terrible Rural Highway	766	0.005	0.013	0.000	0.193

2.5 Annual Vehicle Miles and Heavy Vehicles – Infrastructure Controls

Control variables for the wear and tear of infrastructure include the number of the number of annual vehicle miles per road system and the number of heavy vehicles registered per state.

Data is again collected from the U.S. Department of Transportation's Federal Highway Administration Highway Statistic Series.

Annual Vehicle Miles, which measures the amount of travel for all vehicles per region, comes from the VM-2 report. To make vehicle miles comparable per state, I use Total Lane Miles from the HM-60 report as a measure for the physical size of each state, and divided Annual Vehicle Miles by Total Lane Miles per road.

Table 5: Vehicle Lane Miles Divided by Total Lane Miles (in Thousands)

Statistic	N	Mean	St. Dev.	Min	Max
Total	833	352.674	206.996	41.158	903.399
Total Highways	833	3,038.703	1,291.027	507.660	6,166.072
Total Arterial Roads	833	251.211	139.271	32.827	624.723
Total Rural	833	197.994	108.362	31.353	559.496
Tutal Urban	833	738.510	178.339	140.248	1,309.845
Rural Highways	818	2,116.939	945.379	377.882	5,487.764
Urban Highways	833	4,132.521	1,234.210	886.427	7,224.660
Rural Arterial	833	151.042	89.218	24.141	470.999
Urban Arterial	833	532.279	107.571	108.072	837.049

The final control variable for infrastructure wear and tear is the number of heavy vehicles on the roads. Data on the number of registered trucks, buses and automobiles per state comes from the FHA's Highway Statistic Series MV-1 report. These variables were again converted into proportions by dividing the number of trucks, buses, and automobiles respectively by the total number of registered vehicles to make them comparable across states.

Table 6: State Vehicle Registration Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Trucks	816	0.469	0.087	0.218	0.711
Buses	816	0.003	0.001	0.001	0.009
Automobiles	816	0.520	0.094	0.244	0.776

2.6 Visualization & Discussion

Several trends are immediately identifiable through certain cross sections of the panel. Figure 1 averages and plots the number of corruption convictions per 1 million people between the years 1998 and 2014. We see that the most corrupt state per capita was Louisiana, closely followed by Alaska, Mississippi, South Dakota, North Dakota, Kentucky and Montana, each with an annual average of over 6 convictions per 1 million.

Figure 1: Average Convictions per State

(1998 - 2014)

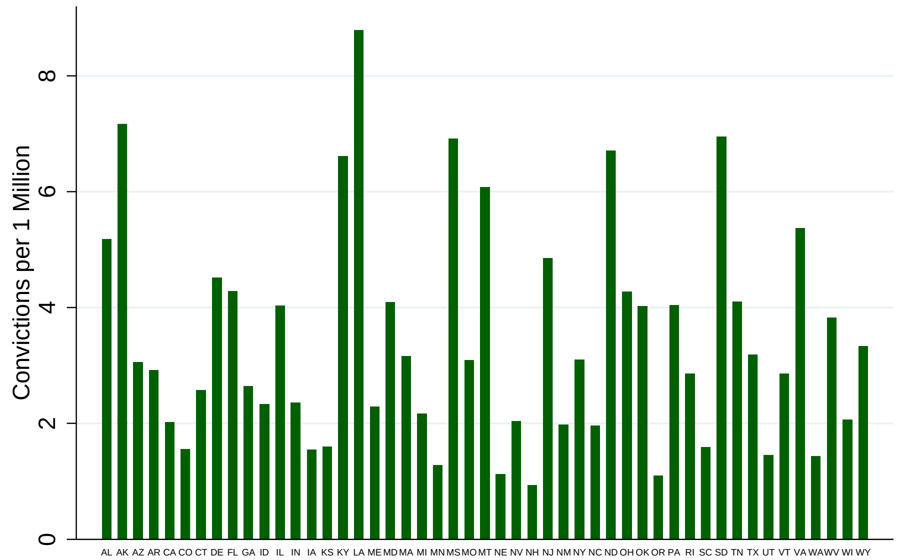


Figure 2 takes the average number of corruption convictions per capita and scatters them against the average annual proportion of construction spending per state. From the plot, we see a potential positive correlation between the proportion of construction spending and the level of corruption per state.

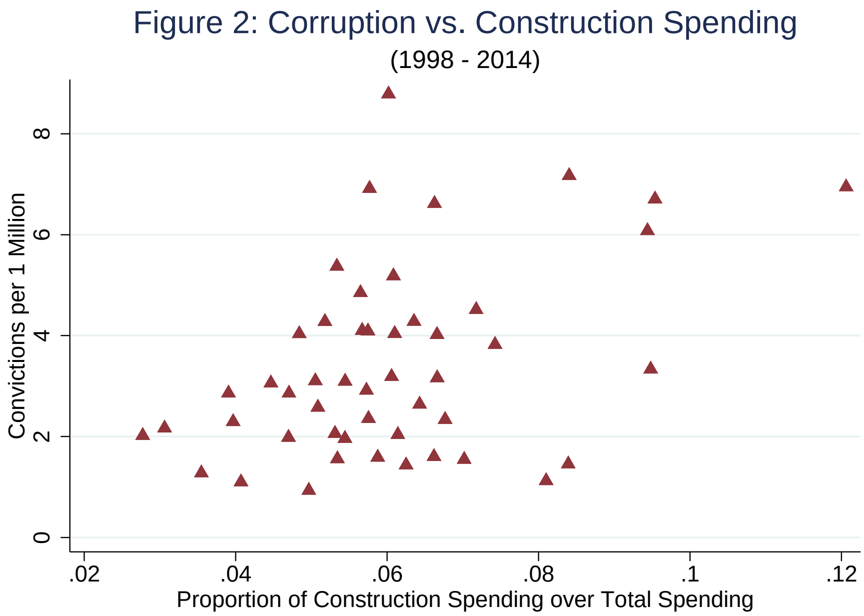
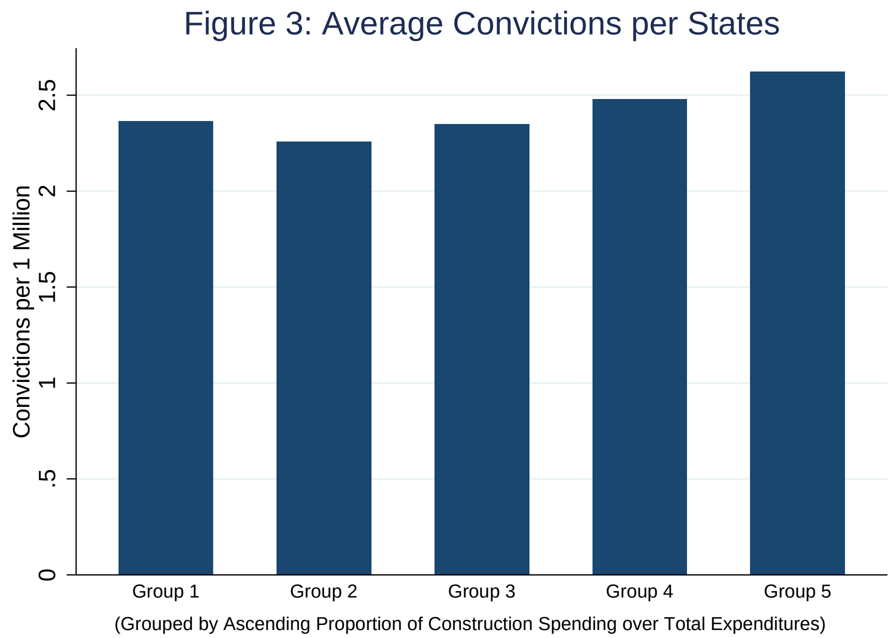


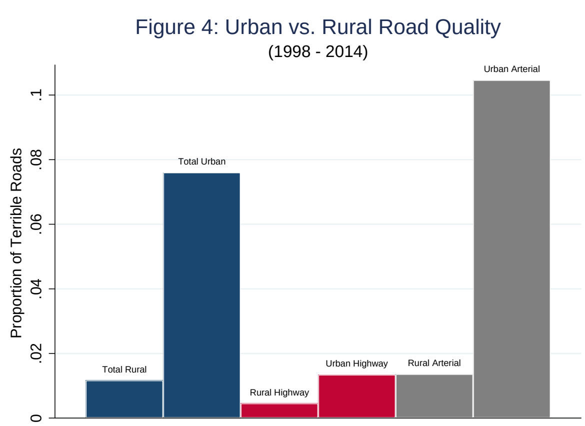
Figure 3 plots the average number of corruption convictions per 1 million in groups of 10. States were ranked by their average proportion of construction spending per total expenditures and aggregated into 5 groups, each with an **increasing** average proportion of construction expenditures.

Group 1 consists of California, Michigan, Minnesota, Vermont, Maine, Oregon, Arizona, New Mexico, Rhode Island and Illinois. These are states with the lowest proportional construction spending. Group 2 is New Hampshire, New York, Connecticut, Ohio, Wisconsin, Virginia, Colorado, North Carolina, Missouri and New Jersey. Group 3 is Tennessee, Arkansas, Maryland, Indiana, Mississippi, South Carolina, Louisiana, Texas, Alabama and Pennsylvania. Group 4 is Nevada, Washington, Florida, Georgia, Kansas, Kentucky, Oklahoma, Massachusetts, Idaho and Iowa. Group 5, which has on average the highest proportion of construction spending, is Delaware, West Virginia, Nebraska, Utah, Alaska, Montana, Wyoming, North Dakota and South Dakota.



Without controlling for other factors, Figure 3 implies that higher levels of construction spending on average associated with higher levels of corruption. Group 2, which is composed of 10 states with the second lowest proportion of construction spending has an annual average of 2.25 convictions per 1 million, while group 5 has an annual average of 2.75 convictions, which is around 22% higher.

Figures 4 and 5 plot comparisons between the average proportions of terrible quality pavement per state. Figure 4 compares Urban and Rural pavement, while Figure 5 compares Highway and Arterial pavement.



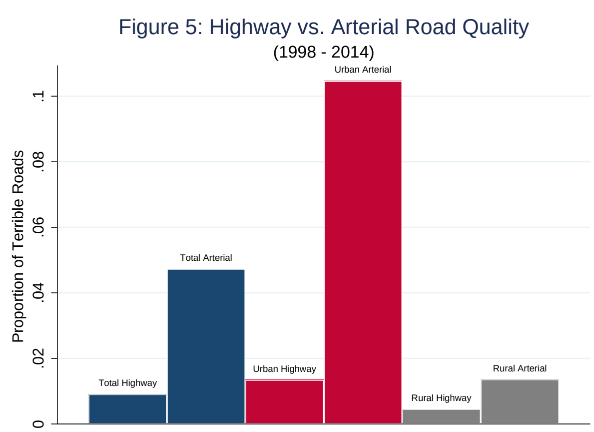
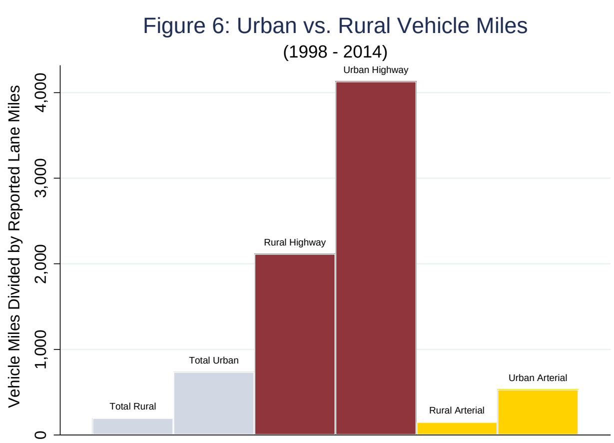
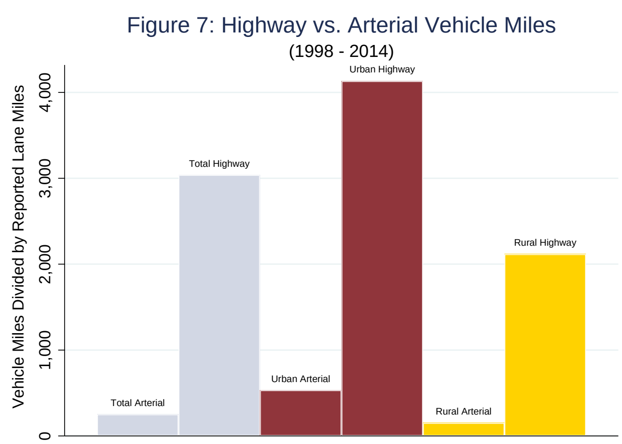


Figure 4 reveals that on average, urban roads have a greater proportion of terrible quality pavement, indicating that **they are in greater need of infrastructure projects for repair**. Similarly, Figure 5 reveals that all types of arterial roads have on average greater proportions of terrible quality pavement when compared to highways.

Figures 6 and 7 compares the relative road use by annual vehicle miles over total lane miles per type of road. Figure 6 compares urban and rural roads use while Figure 7 compares highway and arterial roads use. From Figure 6, we see that all **rural roads show on average less use** than urban roads, while from Figure 7, we see that **arterial roads are much less used** than highways.





3 Empirical Tests & Results

3.1.1 ***<u>Hypothesis I</u>*: *Higher levels of Construction Projects Provide Greater Opportunities for Public Corruption.***

3.1.2 Regression Model

To estimate the effects of construction expenditures on corruption convictions, I estimate the following regression equation: Corruption convictions per 1 million is a function of the proportion of construction spending per state from one period before, and revenue per population is used as a control for the relative size of state budgets.

$$\frac{corruption}{population}_t = \beta_1 \frac{construction}{expenditures}_{t-1} + \alpha_1 \frac{revenue}{population}_t$$

The problem with this equation is that construction is an endogenous variable. To control for the reverse causality, I use a two-stage least squares regression[24], and estimate construction expenditures with two weather-related, exogenously excluded instruments.

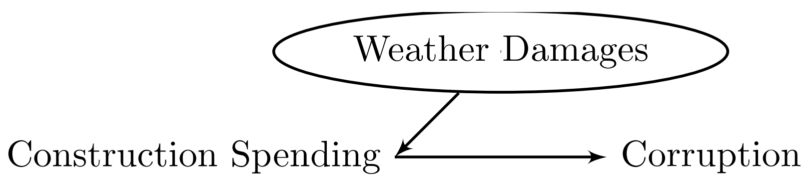


Diagram 5: Causal Diagram with Instrumental Variable

Equations for the two stages are listed below. In stage 1, I first correct endogeneity on the construction variable by estimating it as a function of revenue per population, the average hourly wages of construction laborers, and the average temperature and total rainfall[25]. In stage 2, I then use the estimated value of construction expenditures in place of the original endogenous variable to estimate the exogenous impacts of construction spending on corruption levels.

$$Stage1 : \frac{\widehat{construction}}{expenditures}_{t-1} = \hat{\alpha}_1 \frac{revenue}{population}_{t-1} + \hat{\alpha}_2 wage_{t-1} + \hat{\gamma}_1 temp_{t-2} + \hat{\gamma}_2 rain_{t-2}$$

$$Stage2 : \frac{corruption}{population}_t = \beta_1 \frac{\widehat{construction}}{expenditures}_{t-1} + \alpha_1 \frac{revenue}{population}_t$$

$$\beta_i = ParameterofInterest$$

$$\alpha_i = ControlVariables$$

$$\gamma_i = InstrumentalVariable$$

[24] After conducting a Wald-test, I found that no fixed effects were needed in this direction.
[25] Instruments are both highly correlated with construction spending.

3.1.3 Results & Discussion

Results for the Two-Stage Least Squares Regression in both logs[26] and levels are reported in Table 7.

Table 7: Construction as a Predictor for Corruption

	Dependent variable:	
	Corruption per 1 Million	log(Corruption per 1 Million)
	(1)	(2)
Construction/Expenditures	61.096***	
	(12.591)	
Revenue/Population	0.289***	
	(0.083)	
log(Construction/Expenditures)		0.487***
		(0.165)
log(Revenue/Population)		0.207***
		(0.080)
F Statistic (df = 2; 730)	19.01***	5.256***
Observations	733	733
R^2	0.050	0.014
Adjusted R^2	0.047	0.011
Residual Std. Error (df = 730)	2.943	0.609
Note:	*p<0.1; **p<0.05; ***p<0.01 Robust Standard Errors	

With heteroscedasticity robust standard errors, the corruption coefficient is significant on both regressions, suggesting there is a strong positive relationship between the proportion of construction spending per state and the levels of public corruption. The coefficients on revenue per population are also significant, suggesting that the relative budget size per state also has an impact on predicting construction spending and corruption levels.

From these regressions, I conclude that higher levels of construction on average lead to higher levels of public corruption because of the opportunities and incentives that construction contracts create for corrupt exchanges.

[26] To correct for states that had 0 corruption convictions in certain periods, 1 was added to every observation before taking the logarithmic transformation.

3.2.1 ***Hypothesis II**: Corruption has an Impact on the Locations of State Infrastructure Projects.*

3.2.2 Regression Model

To estimate the effects of corruption on the location and types of infrastructure projects, I use a fixed effects regression to estimate the proportion of *bad* infrastructure as a function of corruption. Significance on the corruption variables will indicate where public funds and infrastructure projects are being allocated.

The general model is listed below, and uses both financial and wear and tear control variables to isolate the effects of corruption. The financial control variable is the proportion of total highway construction expenditures, and the wear and tear control variables are the annual vehicle miles, the proportion of registered trucks, the average temperature and the total annual rainfall per state.

$$\frac{BadInfrastructure}{TotalReported}_{i,t} = \beta_1 \frac{corruption}{population}_{i,t-1} + \alpha_1 \frac{HighwayConstruction}{Expenditures}_{i,t-1} + \alpha_2 \frac{VehicleMiles}{LaneMiles}_{i,t-1} + \alpha_3 \frac{Trucks}{Vehicles}_{i,t-1} + \alpha_4 temp_{i,t-1} + \alpha_5 rain_{i,t-1} + \delta_i$$

$\beta_i = ParameterofInterest$

$\alpha_i = ControlVariables$

$\delta_i = FixedEffectDummies$

3.2.3 Results & Discussion

Regression results with clustered standard errors and statistical significance on the corruption variable are reported below[27] in Table 8.

Table 8: Corruption as a Predictor Pavement Quality

	Dependent variable:				
	Poor Rural	Terrible (Total)	Terrible Arterial	Terrible Rural	Terrible Rural Arterial
	(1)	(2)	(3)	(4)	(5)
Corruption per Capita	−0.001*	−0.001**	−0.001**	−0.001**	−0.001*
	(0.001)	(0.0004)	(0.001)	(0.0004)	(0.001)
Highway Construction/Total	0.042*	0.001	0.001	0.010	0.010
	(0.025)	(0.013)	(0.020)	(0.008)	(0.010)
Rural V.M./L.M.	−0.00004			−0.00000	
	(0.0001)			(0.00003)	
Vehicle Miles/Lane Miles		−0.0001			
		(0.0001)			
Arterial V.M./L.M.			−0.0003**		
			(0.0001)		
Rural Arterial V.M./L.M.					−0.00000
					(0.0001)
Proportion of Trucks	−0.138***	0.170***	0.307***	−0.021	−0.016
	(0.047)	(0.034)	(0.045)	(0.016)	(0.021)
Average Temperature	−0.00003	−0.001	−0.002*	0.0002	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Average Rainfall	−0.0003	0.00002	0.0001	−0.00005	−0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	717	717	717	717	717
R^2	0.058	0.163	0.237	0.038	0.034
Adjusted R^2	−0.019	0.095	0.175	−0.041	−0.045
F Statistic (df = 6; 662)	6.818***	21.515***	34.279***	4.312***	3.838***
Note:	*p<0.1; **p<0.05; ***p<0.01 Clustered Standard Errors				

Results reveal that corruption has some impact on the location of certain pavement projects[28]. After controlling for both infrastructure spending and road usage, there is reasonable evidence that increases in corruption lead to improvements in the road quality[29], but only those concentrated in rural and arterial roads.

[27] All raw regressions, including those without significance on the corruption variable, are reported in the Appendix.
[28] Preliminary regressions reported in the Appendix suggest that corruption has no significant impact on bridges, urban roads or highways.
[29] Corruption may also be endogenous with infrastructure quality, as corruption increases construction spending.

These results are interesting, because while evidence from Figures 4, 6 and 7 show that urban roads are in the most need of repair, and that urban roads and highways are the most heavily used, these roads have no significant correlation with corruption[30]. Instead, it is rural pavement that *improves* by about 4% when public corruption increases by one conviction per 1 million in population. This suggests that funds are not being allocated to address the roads with the heaviest need, but perhaps instead are being concentrated in areas with less use and less public scrutiny.

These results are consistent with theory, which stresses the idea that corrupt public officials prefer to fund projects that provide greater benefits to themselves than the public. If corrupt officials maximize their personal benefits by awarding construction contracts, and if they favor projects with less regulatory risk and oversight, it seems natural for them to choose pavement projects confined to rural and arterial areas over those in areas with higher amounts of traffic. The results suggest that while public corruption increases average construction spending, these increases are not being allocated in a socially optimal way.

4 Concluding Remarks

This paper finds that there is a statistically significant relationship between state level federal corruption convictions and infrastructure projects. It finds that public construction projects create both incentives and opportunities for public corruption, as small increases in the amount of infrastructure spending lead to substantial increases in corruption convictions. This result is particularly interesting because it demonstrates that there exist completely exogenous causes of public corruption—that areas prone to natural disasters, flooding, and other weather related damages are naturally going to have higher average corruption levels than those that are

[30] See Tables 10 – 15 in the Appendix

not, regardless of cultural norms, voting blocs or government institutional structures. Again, this is due to the close regulatory relationship between governments and construction projects, as well as the market structures of local construction industries.

This paper also finds that corrupt officials are more likely to allocate public funds into unnecessary infrastructure projects for roads that are both less used and less damaged. This result is significant because it captures one of the qualitative aspects of public corruption on state infrastructure, and explains why in certain regions, despite experiencing consistent traffic due to construction projects, pavement quality in key areas does not improve.

While this study evaluates the location of infrastructure projects under corrupt officials, due to data restrictions, it cannot measure the quality of the projects themselves. At the time being, there is no streamlined way of measuring and comparing the efficiencies of public projects using metrics even as simple as how much a project should have cost relative to how much it did cost on a large geographical scale. The best we can do for now is use total construction spending over total expenditures as an explanatory variable. Future work will likely be able to more accurately explore the implications of public corruption on the quality of infrastructure projects as opposed to simply the quality of the infrastructure itself.

5 Appendix

Table 9: Corruption as a Predictor of Bridge Quality

	Dependent variable:		
	p_defunct	p_structdefunct	p_fobsolete
	(1)	(2)	(3)
lag.convictpercap	−0.0003	−0.0003	0.00003
	(0.0003)	(0.0003)	(0.0002)
lag.highwayconstruct_total	0.021**	0.022***	−0.0001
	(0.009)	(0.008)	(0.005)
lag.vmlane	−0.00004	−0.00004	0.00000
	(0.00005)	(0.00004)	(0.00003)
lag.p_trucks	−0.341***	−0.215***	−0.127***
	(0.018)	(0.017)	(0.010)
lag.averagetemp	0.002***	0.001*	0.001**
	(0.001)	(0.001)	(0.0004)
lag.avgrainfall	0.00003	−0.00000	0.00003
	(0.0001)	(0.0001)	(0.0001)
Observations	767	767	767
R^2	0.373	0.231	0.191
Adjusted R^2	0.326	0.173	0.129
F Statistic (df = 6; 712)	70.643***	35.715***	27.942***
Note:	*p<0.1; **p<0.05; ***p<0.01		
	Non-Clustered Standard Errors		

Table 10: Corruption as a Predictor of Total Poor Road Quality

	Dependent variable:		
	p_pavement_total	p_highway	p_artlocal
	(1)	(2)	(3)
lag.convictpercap	-0.001^{*}	-0.0004	-0.001
	(0.001)	(0.0004)	(0.001)
lag.highwayconstruct_total	0.008	0.003	-0.002
	(0.016)	(0.011)	(0.024)
lag.vmlane	-0.0002^{**}		
	(0.0001)		
lag.highwayvmlane		0.00000	
		(0.00001)	
lag.artlocalvmlane			-0.0004^{***}
			(0.0001)
lag.p_trucks	0.202^{***}	-0.049^{**}	0.464^{***}
	(0.033)	(0.022)	(0.047)
lag.averagetemp	-0.002^{*}	0.0003	-0.006^{***}
	(0.001)	(0.001)	(0.002)
lag.avgrainfall	-0.0002	-0.00002	-0.00001
	(0.0003)	(0.0002)	(0.0004)
Observations	717	717	717
R^2	0.059	0.010	0.144
Adjusted R^2	-0.018	-0.071	0.074
F Statistic (df = 6; 662)	6.935^{***}	1.133	18.592^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Non-Clustered Standard Errors

Table 11: Corruption as a Predictor of Urban Poor Road Quality

	Dependent variable:		
	p_urban	p_u_highway	p_u_artlocal
	(1)	(2)	(3)
lag.convictpercap	0.0001	−0.001	0.0004
	(0.001)	(0.001)	(0.001)
lag.highwayconstruct_total	0.030	0.005	0.045
	(0.022)	(0.014)	(0.029)
lag.urbanvmlane	0.0001		
	(0.0001)		
lag.uhighwayvmlane		0.00001***	
		(0.00001)	
lag.uartlocalvmlane			0.0001
			(0.0001)
lag.p_trucks	−0.054	−0.120***	0.010
	(0.047)	(0.028)	(0.064)
lag.averagetemp	−0.001	0.001	−0.002
	(0.002)	(0.001)	(0.002)
lag.avgrainfall	0.0002	−0.00000	0.0002
	(0.0004)	(0.0002)	(0.0005)
Observations	717	717	717
R^2	0.010	0.041	0.009
Adjusted R^2	−0.070	−0.037	−0.071
F Statistic (df = 6; 662)	1.145	4.757***	1.042
Note:	*p<0.1; **p<0.05; ***p<0.01		
	Non-Clustered Standard Errors		

Table 12: Corruption as a Predictor of Rural Poor Road Quality

	Dependent variable:		
	p_rural	p_r_highway	p_r_artlocal
	(1)	(2)	(3)
lag.convictpercap	-0.001^{**}	-0.0002	-0.001^{**}
	(0.001)	(0.0004)	(0.001)
lag.highwayconstruct_total	0.042^{***}	-0.006	0.039^{**}
	(0.015)	(0.012)	(0.019)
lag.ruralvmlane	-0.00004		
	(0.0001)		
lag.rhighwayvmlane		-0.00001	
		(0.00001)	
lag.rartlocalvmlane			-0.0001
			(0.0001)
lag.p_trucks	-0.138^{***}	-0.032	-0.131^{***}
	(0.031)	(0.023)	(0.039)
lag.averagetemp	-0.00003	-0.0005	0.0002
	(0.001)	(0.001)	(0.002)
lag.avgrainfall	-0.0003	-0.00004	-0.0004
	(0.0002)	(0.0002)	(0.0003)
Observations	717	703	717
R^2	0.058	0.005	0.036
Adjusted R^2	-0.019	-0.076	-0.043
F Statistic	6.818^{***} (df = 6; 662)	0.598 (df = 6; 649)	4.073^{***} (df = 6; 662)
Note:	*p<0.1; **p<0.05; ***p<0.01 Non-Clustered Standard Errors		

Table 13: Corruption as a Predictor of Total Terrible Road Quality

	Dependent variable:		
	t_total	t_highway	t_artlocal
	(1)	(2)	(3)
lag.convictpercap	-0.001^{***}	-0.0003^{**}	-0.001^{***}
	(0.0003)	(0.0002)	(0.0004)
lag.highwayconstruct_total	0.001	-0.002	0.001
	(0.008)	(0.004)	(0.012)
lag.vmlane	-0.0001^{***}		
	(0.00004)		
lag.highwayvmlane		0.00000	
		(0.00000)	
lag.artlocalvmlane			-0.0003^{***}
			(0.0001)
lag.p_trucks	0.170^{***}	0.006	0.307^{***}
	(0.015)	(0.009)	(0.023)
lag.averagetemp	-0.001	0.0003	-0.002^{**}
	(0.001)	(0.0004)	(0.001)
lag.avgrainfall	0.00002	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0002)
Observations	717	717	717
R^2	0.163	0.012	0.237
Adjusted R^2	0.095	-0.068	0.175
F Statistic (df = 6; 662)	21.515^{***}	1.388	34.279^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01		
	Non-Clustered Standard Errors		

Table 14: Corruption as a Predictor of Urban Terrible Road Quality

	Dependent variable:		
	t_urban	t_u_highway	t_u_artlocal
	(1)	(2)	(3)
lag.convictpercap	0.0002	−0.0003*	0.0003
	(0.0005)	(0.0002)	(0.001)
lag.highwayconstruct_total	0.016	0.001	0.022
	(0.013)	(0.006)	(0.019)
lag.urbanvmlane	0.00001		
	(0.00003)		
lag.uhighwayvmlane		0.00001**	
		(0.00000)	
lag.uartlocalvmlane			0.0001*
			(0.0001)
lag.p_trucks	0.042	0.001	0.091**
	(0.028)	(0.011)	(0.041)
lag.averagetemp	−0.0005	0.0004	−0.001
	(0.001)	(0.0005)	(0.002)
lag.avgrainfall	0.0001	0.0001	0.0001
	(0.0002)	(0.0001)	(0.0003)
Observations	717	717	717
R^2	0.005	0.015	0.010
Adjusted R^2	−0.076	−0.065	−0.070
F Statistic (df = 6; 662)	0.577	1.708	1.161
Note:	*p<0.1; **p<0.05; ***p<0.01		
	Non-Clustered Standard Errors		

Table 15: Corruption as a Predictor of Rural Terrible Road Quality

	Dependent variable:		
	t_rural	t_r_highway	t_r_artlocal
	(1)	(2)	(3)
lag.convictpercap	−0.001***	−0.0002	−0.001***
	(0.0002)	(0.0002)	(0.0002)
lag.highwayconstruct_total	0.010*	−0.004	0.010
	(0.005)	(0.005)	(0.007)
lag.ruralvmlane	−0.00000		
	(0.00002)		
lag.rhighwayvmlane		−0.00000	
		(0.00000)	
lag.rartlocalvmlane			−0.00000
			(0.00003)
lag.p_trucks	−0.021*	0.005	−0.016
	(0.011)	(0.009)	(0.014)
lag.averagetemp	0.0002	−0.0001	0.001
	(0.0004)	(0.0004)	(0.001)
lag.avgrainfall	−0.00005	0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)
Observations	717	703	717
R^2	0.038	0.006	0.034
Adjusted R^2	−0.041	−0.075	−0.045
F Statistic	4.312*** (df = 6; 662)	0.639 (df = 6; 649)	3.838*** (df = 6; 662)
Note:	*p<0.1; **p<0.05; ***p<0.01		
	Non-Clustered Standard Errors		

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