Don’t Blame the Weather: Federal Natural Disaster Aid and Public Corruption

Adriana Cordis and Jeff Milyo

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Abstract

Previous research using data on convictions for corruption-related crimes from the Public Integrity Section (PIN) of the Department of Justice points to a positive correlation between the amount of corruption in a state and the amount of federal funds provided to the state for natural disaster relief. We take a closer look at the relationship between public corruption and disaster assistance, using more detailed data on corruption convictions for an expanded time period. Our analysis provides little support for the hypothesis that the provision of federal disaster aid increases public corruption. It suggests instead that prior evidence of such a link arises from an unexplained correlation during the 1990s between disaster aid and convictions of postal employees for crimes such as stealing mail. Convictions for postal service crimes appear to account for a large fraction of the total federal convictions reported by PIN, which could have far-reaching implications given that the PIN data have been used so extensively in the corruption literature.

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Author Affiliation and Contact Information

Adriana Cordis
Assistant Professor
Department of Accounting, Finance, and Economics
Winthrop University
cordisa@winthrop.edu

Jeff Milyo
Professor
Department of Economics
University of Missouri
milyoj@missouri.edu

Don't Blame the Weather

Federal Natural Disaster Aid and Public Corruption

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1. Introduction

Do episodes of extreme weather conditions contribute to the geographic patterns in public corruption across the United States? Leeson and Sobel (2008) argue that they do. Using data culled from the annual report to Congress by the Public Integrity Section (PIN) of the Department of Justice (DOJ), they show that convictions for public corruption are substantially higher in states that are frequently hit by natural disasters, such as those along the US Gulf Coast. Leeson and Sobel argue that this finding has a simple explanation: the influx of federal aid that follows in the wake of a natural disaster creates many new opportunities for fraudulent appropriation by public officials, thereby increasing corruption.

In this study, we use a new and more detailed dataset to revisit the relationship between federal disaster aid and public corruption. Although the PIN data employed by Leeson and Sobel (2008) have been used extensively in the empirical literature, they are not particularly well suited to testing the hypothesis that disaster aid promotes public corruption. If bad weather indirectly leads to an increase in corruption via the disaster aid channel, then we would expect the relationship between the amount of federal disaster aid received by a state and the number of public officials convicted of corruption-related offenses to manifest itself primarily among state and local officials. This expectation arises from the manner in which the Federal Emergency Management Agency (FEMA) oversees and distributes disaster aid.

Once an official disaster declaration has been issued, FEMA takes the lead role in coordinating federal disaster relief. Disaster aid funds are provided directly to individuals, to state governments, and to local governments. Although some FEMA officials and some officials at other federal agencies that also distribute disaster aid might themselves be involved in corruption, we would not expect most federal officials who work within a state to have significant opportunities to fraudulently appropriate disaster relief funds. To the extent that federal aid creates new opportunities for public corruption, we expect these opportunities to be highly concentrated in state and local government agencies.

Most of the anecdotal evidence cited by Leeson and Sobel (2008) is consistent with this view. For example, they note that after flooding in Buchanan County, Virginia, in 2002, "county officials embarked on a frenzy of bribe solicitation for relief-related reconstruction contracts that ended in 16 indictments for public corruption." Because the PIN data used by Leeson and Sobel (2008) do not distinguish between federal, state, and local officials, their findings could be influenced by the presence of a large number of federal officials in the dataset, which account for about half of all PIN corruption convictions. In addition, Cordis and Milyo (forthcoming) identify several other issues that raise concerns about the reliability of the PIN data.

First, the numbers presented in the annual PIN report to Congress are not internally consistent. The aggregate annual number of convictions listed in the report does not match the number of convictions obtained by aggregating the district-level data in the report, and there are large unexplained swings in the former number over time. Second, the aggregate annual number of convictions from the PIN report is much larger than the aggregate annual number of convictions shown in the statistical report of the Executive Office for United States Attorneys (EOUSA). Cordis and Milyo (forthcoming) argue that the most likely source of this discrepancy is that the PIN data include a large number of convictions of postal service employees for stealing and destroying mail. Although destroying, stealing, or tampering with mail is a federal crime, it is not corruption as it is usually described in the literature.

To overcome these shortcomings of the PIN data, we conduct our analysis using a new dataset obtained from the Transactional Records Access Clearinghouse (TRAC), a research organization affiliated with Syracuse University. The TRAC database contains records on all publicly available criminal cases in federal courts, including offenses by federal, state, and local public employees for official misconduct or misuse of office. These data can be disaggregated down to the individual case level, making it possible to analyze corruption by referrals, convictions, and penalties imposed, and to segment convictions by type of charge, type of public official, and geographic district. The ability to do so allows us to test the Leeson and Sobel (2008) hypothesis using convictions for FEMA, state, and local officials (i.e., using a convictions series that excludes all non-FEMA federal officials). Not only is this aspect of the TRAC data important for our analysis, it will likely be a boon for future empirical research on the causes and consequences of public corruption.

We begin the empirical analysis by replicating the Leeson and Sobel (2008) panel data regressions for their sample period, which covers the years 1990–1999. The results of these regressions using the PIN data are very similar to those that they report. The coefficient estimates point to a statistically significant relationship between the amount of federal disaster aid received by a state in a given year and the number of corruption convictions in the next few years. In addition, this relationship appears to be relatively robust to the use of different regression specifications and sets of controls.

Next, we fit the panel data regressions using the federal, state, and local convictions for 1990–1999 from TRAC as the dependent variable instead of the PIN convictions series. The results look strikingly different from those obtained with the PIN data. None of the estimated coefficients on the amount of federal disaster aid is statistically significant, and many of the point estimates are actually negative. These findings are also robust to the use of different regression specifications and sets of controls.

Because the PIN convictions series contains many more convictions than the TRAC convictions series, our analysis suggests that the Leeson and Sobel (2008) findings are driven by federal convictions for postal service crimes that are included in the PIN data but not in the TRAC data. The absence of a plausible explanation for why federal disaster aid would be tied to such crimes casts the regression results for the 1990–1999 sample period in an interesting light. Without such an explanation, it seems reasonable to question whether the hypothesized relationship between federal disaster aid and public corruption truly explains these results.

To investigate further, we estimate all the panel regressions a second time using both the PIN data and TRAC data for 1986–2008. The results using this longer sample period are more consistent across the two different convictions series. Unlike for the 1990–1999 sample period, the regressions that use the PIN convictions series for this period produce little evidence of a relationship between the amount of federal disaster aid and public corruption. Only one of the point estimates of the coefficients on the disaster aid variable is statistically significant at the 5 percent level. Similarly, the regressions using the TRAC data produce no statistically significant coefficient estimates.

It is apparent from this analysis that results obtained using the PIN data are not robust to the choice of sample period. Moreover, it can be argued that one should give the results for the longer sample period more weight in evaluating the totality of the evidence because the regression coefficients are estimated much more precisely using a larger sample. Of course, our findings in this regard might be influenced by the presence of convictions of non-FEMA federal officials in both the PIN and TRAC data. We therefore repeat the analysis using the most relevant measure of corruption for the Leeson and Sobel (2008) hypothesis: convictions for FEMA, state, and local officials.

The panel data regressions using this measure of corruption produce no evidence whatsoever of a relationship between the amount of federal disaster aid and public corruption. The point estimates of the coefficients on the disaster aid variable are small in magnitude, many of them are negative, and none of them is statistically significant. Although this finding is not dispositive, we believe that it raises substantial doubts about the overall economic significance of any corruption that is causally linked to the provision of federal disaster aid.

The unprecedented surge in federal disaster aid in the wake of Hurricane Katrina yields additional evidence in this regard. Leeson and Sobel (2008) highlight the potential impact of this aid on the Gulf Coast region in their concluding remarks, stating that "the magnitude of Katrina-related disbursements, coupled with the results of our analysis, suggest a considerable spike in this region's already significant corruption level." To see whether the convictions data bear out this prediction, we plot each of the corruption convictions series for the years 2000–2010 for the five states with the largest amounts of disaster aid per capita in 2005: Louisiana, Mississippi, Alabama, Florida, and Texas.

The plots reveal that the predicted spike in corruption never materialized, at least as measured by the convictions data. The average level of convictions for the pre-Katrina years is similar to that for the post-Katrina years. There is some suggestion of an increase in corruption using the PIN conviction series, but nothing like a spike. Moreover, there is no clear indication of an increase for the TRAC series that includes convictions for all federal, state, and local officials, or for the TRAC series that includes convictions for state, local, and FEMA officials. This is in spite of the monumental scale of the post-Katrina disaster relief effort. Naturally, we are mindful of the well-worn caveat about an absence of evidence not being the same as evidence of absence. In our view, however, we should not "blame the weather" for exacerbating public corruption without much more definitive empirical evidence than is provided by the data.

More broadly, our findings potentially have far-reaching implications given that the PIN data have been used so extensively in the corruption literature. If, as our analysis suggests, the evidence of a relationship between federal disaster aid and corruption convictions for the 1990–1999 sample period is driven by the inclusion of convictions for crimes by postal service workers in the PIN data, then our analysis raises the question of whether other empirical findings might be influenced by the presence of these convictions as well.

2. Description of the Data

We use a panel dataset that contains annual observations for the 50 states for the years 1986–2008. The dependent variable in the panel regressions is a measure of the annual number of corruption convictions for each state per 100,000 residents. The explanatory variables are the annual per capita federal disaster aid to each state, which is measured in hundreds of constant 2010 dollars per resident, and a number of controls.

2.1. *Data on Corruption Convictions*

The data on corruption convictions are drawn from two distinct sources. The first is the annual report to Congress by the PIN of the DOJ.[1] This is by far the most commonly used source of convictions data for empirical research on corruption and the data source used by Leeson and Sobel (2008). The second is the Transactional Records Access Clearinghouse (TRAC), a research organization affiliated with Syracuse University.[2] The TRAC organization maintains a comprehensive database that contains records on all publicly available criminal cases prosecuted in federal courts, including cases brought against federal, state, and local public employees for offenses related to official misconduct or misuse of office.

2.1.1. The PIN data. The PIN data have been used extensively in empirical research on corruption in the United States.[3] They have the advantage of being freely available from the annual reports to Congress by the DOJ. However, as Cordis and Milyo (forthcoming) point out, there are a number of issues with these data that raise concerns about their reliability.

One aspect of the PIN data that seems to have gone largely unnoticed is that they are compiled from a survey of US Attorneys that allows for some subjectivity in classifying cases. Starting in 1983, the questionnaire sent to the US Attorneys encouraged the reporting of any criminal activity involving abuse of office by public officials, including lower-level employees and minor crimes. Specifically, according to the 1983 DOJ report to Congress, the questionnaire states, "For purposes of this questionnaire, a public corruption case includes any case involving

[1] Table 3 of the report lists convictions by judicial district. We aggregate these data to obtain an annual state-level measure of corruption.
[2] We obtained this data under license from TRACfed (http://tracfed.syr.edu/).
[3] See, e.g., Adsera, Boix and Payne (2003), Alt and Lassen (2008), Cordis (2009), Dincer, Ellis and Waddell (2010), Fisman and Gatti (2002), Glaeser and Saks (2006), Goel and Nelson (1998), Goel and Nelson (2011), Hill (2003), Johnson, LaFountain and Yamarik (2011), Leeson and Sobel (2008), and Schlesinger and Meier (2002).

abuse of office by a public employee. We are not excluding low-level employees or minor crimes, but rather focusing on the job-relatedness of the offense and whether the offense involves abuse of the public trust placed in the employee."

Cordis and Milyo (forthcoming) find that this change in the survey instructions resulted in a dramatic increase in the number of public corruption convictions reported in the PIN data. It is unclear, however, whether the additional convictions are for crimes that we would typically view as public corruption. Starting in 1986, information contained in the statistical report of the EOUSA can be used to cross-check the aggregate annual corruption convictions reported by PIN. The PIN conviction series from 1986 onward contains a large number of convictions that do not show up in the EOUSA report. Cordis and Milyo (forthcoming) cross-check the EOUSA data against the TRAC data, which is discussed in more detail below, and find that these two sources are in very close agreement.

Two potential explanations for this finding immediately come to mind. One possibility is that the PIN surveys capture corruption among lower-level government officials that are simply not reported by the EOUSA and TRAC. If this is the case, then it follows that hundreds of federal prosecutions of lower-level government officials each year for corruption are not included in the TRAC database. Cordis and Milyo (forthcoming) conduct an extensive search of news reports in an effort to find evidence of such prosecutions and uncover none. The lack of such evidence leads us to consider a second possibility: that the US Attorneys in various districts are reporting crimes in the PIN survey that TRAC does not classify as public corruption.

Cordis and Milyo (forthcoming) argue that this is likely a key reason for the discrepancy between the two convictions series. Through a Freedom of Information Act request, they obtained copies of a number of PIN surveys filled out by federal prosecutors. The completed surveys list a surprisingly large number of convictions of postal service employees for crimes such as destroying or stealing mail. This audit of survey contents suggests such offenses could account for more than half of all the federal corruption convictions reported to PIN. Although destroying or stealing mail is a federal crime, it does not fit with the usual descriptions of corrupt practices found in the literature.

Cordis and Milyo (forthcoming) also note that there are other issues that call the reliability of the PIN data into question. For example, they take the convictions listed by judicial district in table 2 of the annual PIN report to Congress, aggregate these convictions across all districts, and compare the results to the aggregate number of convictions listed in table 3 of the same report. These two numbers are strikingly different for many of the years before 1994. This does not instill much confidence in the data quality.[4]

Putting aside questions about reliability, another issue suggests the PIN data may not be well suited to testing the hypothesis that federal disaster aid promotes corruption. If disaster relief leads to additional corruption, then we would expect the relationship between the amount of federal disaster aid received by a state and the number of public officials convicted for corruption-related offenses to manifest itself primarily among state and local officials (see section 3.3 for further discussion). Because the PIN data do not distinguish between federal, state, and local officials, there is no way to exclude convictions of federal officials from the convictions series used to test the Leeson and Sobel (2008) hypothesis. This could easily affect the empirical findings, given that federal officials account for more than half of all corruption convictions.

[4] We show in section 3 that substituting the TRAC convictions series for the PIN convictions series substantially alters our inferences about the relationship between corruption and the provision of federal disaster aid. This is the case even if we exclude the data for years before 1994 from the analysis. Hence, the data inconsistencies noted by Cordis and Milyo (forthcoming) do not appear to explain our findings in this regard.

2.1.2. The TRAC data. One of the advantages of the TRAC database is that it provides much more detailed information about corruption cases than can be gleaned from the annual PIN report to Congress. For example, it provides information on lead statutory charges. The most frequent lead charges are "Theft or Bribery in Programs Receiving Federal Funds" (18 U.S.C. 666), "Public Money, Property or Records" (18 U.S.C. 641), "Bribery of Public Officials and Witnesses" (18 U.S.C. 201), and "Hobbs Act" (18 U.S.C. 1951). About 60 percent of TRAC corruption convictions for our sample period are of federal officials; the remaining are of state and local officials. Examples of public officials convicted in the corruption cases include legislators, governors, city mayors, state agency heads, and members of their staffs.

We believe that the TRAC data provide the most comprehensive and detailed look at public corruption in the United States that is currently available. TRAC employees make extensive use of Freedom of Information Act requests to ensure that they have all available information on corruption cases and perform a range of quality checks to identify and correct any anomalies or inconsistencies in the data.[5] Unlike the PIN annual report to Congress, the TRAC database reports not only the number of convictions, but also the number of referrals, prosecutions filed, and cases declined. More importantly from our perspective, it categorizes the officials convicted of corruption by level of government and by agency. The ability to isolate specific categories of officials makes the TRAC data especially well suited to testing the hypothesis that federal disaster aid promotes corruption.

We use two corruption series derived from the TRAC data for the empirical analysis. The first measures the per capita number of federal, state, and local officials convicted for corrupt acts, and the second measures the per capita number of FEMA, state, and local officials

[5] See Long, Roberge, Lamicela and Murugesan (2004) for a description of strategies used by TRAC employees to ensure data quality.

convicted for corrupt acts (i.e., it excludes non-FEMA federal officials).[6] One potential limitation of these data (and the PIN data as well) is that the convictions are solely for prosecutions brought in federal courts. Because there is no comprehensive database of public corruption cases, the percentage of cases handled by state and local authorities is impossible to determine with certainty. However, the results of Cordis and Milyo (forthcoming) suggest that it is relatively small. They collect data on state and local prosecutions of public corruption from media reports and find that the evidence suggests over 95 percent of all public corruption cases are prosecuted in federal courts.

2.2. *Data on Federal Disaster Relief*

The data on federal disaster relief were obtained through the Public Entity Risk Institute (PERI). Specifically, we downloaded the data from the PERI Presidential Disaster Declaration website, which was created by the University of Delaware with funding from PERI. Although the website is no longer actively maintained, we base our analysis on a dataset that was created in August 2012 while it was still active.

The PERI database was compiled using official information provided by FEMA in successive updates in 1994, 1997, 2001, 2003, 2005, 2006, and 2008, and includes the amount of federal disaster aid provided to each state annually for the years 1953–2008. These amounts include expenditures on all declared major disasters, including floods, tornadoes, hurricanes, earthquakes, severe freezing, fires, and so on. To obtain a measure of annual FEMA relief per capita, we divide the annual amount of aid provided to each state measured in constant 2010 dollars by the state population.

[6] We include convictions of FEMA officials in this measure and assess whether adding convictions of SBA and USDA officials has any impact on our findings as part of our robustness tests.

2.3. *Regression Specifications*

Our primary method for investigating the relationship between federal disaster aid and corruption convictions is by fitting several variants of the panel regression specification

$$ConvicRate_{s,t} = \delta_t + \gamma_s + \beta_1 FEMA_{s,t-1} + \beta_2 FEMA_{s,t-2} + \beta_3 FEMA_{s,t-3} + X'_{s,t}\lambda + \varepsilon_{s,t},$$

where $ConvicRate_{s,t}$ is the number of corruption convictions per 100,000 residents for state s in year t, δ_t and γ_s denote state and year-fixed effects, $FEMA_{s,t}$ is the federal disaster aid in hundreds of dollars per capita for state s in year t, and $X_{s,t}$ is a vector that contains our control variables for state s in year t. Our controls follow Leeson and Sobel (2008). We use measures of state population, average income, and the share of the state workforce that consists of federal and state employees. We do not include institutional, political, cultural, and other demographic variables that are unlikely to vary significantly over time. However, we control for the impact of these kinds of variables on corruption by including state and year-fixed effects in all the regressions.

2.4. *Descriptive Statistics*

Table 1 (page 30) provides descriptive statistics for all the variables used in the empirical analysis.[7] Even a cursory look at the corruption data reveals notable differences between the PIN and TRAC corruption series. The mean of the PIN convictions series across all states for the years 1986–2008 is 0.33 convictions per 100,000 residents, while that for the corresponding TRAC series is only 0.18 convictions per 100,000 residents. This is consistent with the findings of Cordis and Milyo (forthcoming) regarding the disparity between the PIN and TRAC

[7] Both the FEMA disaster aid data and the corruption convictions data are quite lumpy. The fraction of state-year observations that are zero is 46 percent for FEMA disaster aid, 18 percent for TRAC convictions of federal, state, and local officials, and 9 percent for PIN convictions.

convictions data. The mean for the TRAC series that measures convictions of FEMA, state and local officials is only 0.07 convictions per 100,000 residents.

According to the PIN data, the most corrupt states for our sample period are North Dakota, Louisiana, Mississippi, and South Dakota, with 0.80, 0.70, 0.69, 0.64 average annual convictions per 100,000 residents. In comparison, the TRAC data for federal, state, and local officials indicate that Montana, Alaska, North Dakota, and Mississippi are the most corrupt states, with 0.50, 0.45, 0.44, and 0.40 average annual convictions per 100,000 residents. The rankings change slightly when we measure corruption by the number of convictions of FEMA, state, and local officials. Using this narrower measure, the most corrupt states are Montana, North Dakota, Mississippi, and New Jersey, with 0.33, 0.25, 0.24, and 0.19 average annual convictions per 100,000 residents.

The FEMA relief per capita series has a mean across all states for the years 1986–2008 of 0.20 hundred dollars per resident. However, it is highly skewed. The maximum value is 68.09 hundred dollars per resident. Not surprisingly, FEMA relief is not distributed very evenly through time for most states. Louisiana received a total of $33.5 billion in disaster relief for 1986–2008. Of this total, $30.6 billion was received in 2005, the year of Hurricane Katrina. Similarly, Mississippi received $10.9 billion of its $11.5 billion total in 2005, and Florida received about 70 percent of its total relief in 2004–2005 following a long series of hurricanes that hit the state. Overall, the states of Louisiana, Mississippi, North Dakota, and Florida, which were struck by a total of 115 major natural disasters, received the most FEMA disaster relief per capita, and the states of Rhodes Island, Wyoming, Colorado, and Utah, which were struck by only 16 major natural disasters, received the least amount of relief per capita.

3. Empirical Results

The hypothesis that federally provided disaster aid creates new opportunities for fraudulent appropriation by public officials has at least two key implications. First, it implies that the provision of disaster aid to a given state during a given year should cause the underlying public corruption level in that state to increase, all else being equal. This in turn should cause the number of public officials convicted for corruption in the state to rise in subsequent years. Second, it implies that the average level of federal disaster aid provided to each state over time should to some extent explain the observed differences in the average number of convictions of public officials for corruption across states.

We begin the empirical analysis by taking a brief look at a plot that first appeared in Leeson and Sobel (2008). Figure 1 (page 31) shows the relationship between the average annual number of corruption convictions per 100,000 state residents for 1990–1999 and the total number of declared natural disasters for the state over the 1953–2008 period. The plot in panel A is for the PIN convictions series. As expected, this plot looks very similar to figure 1 of Leeson and Sobel (2008). There appears to be a positive, albeit noisy, relationship between the two variables. States with more natural disasters have more corruption convictions per capita on average. This clearly suggests the potential for a relationship between federal disaster aid and corruption.

3.1. *Regressions for the 1990–1999 Sample Period*

In table 2 (page 32) we replicate and extend the panel data regressions reported in tables 1 and 2 of Leeson and Sobel (2008). Panel A is for a simple specification with only state and year-fixed effects (no controls) using the PIN convictions series for 1990–1999. The initial three columns report the coefficient estimates for a regression of the annual number of corruption convictions per 100,000 state residents on the first lag (column 1), first and second lags (column 2), and first, second, and third lags (column 3) of the FEMA relief per capita. The results in column 1 are consistent with those reported in table 1 of Leeson and Sobel (2008). Specifically, the estimated coefficient on the first lag of FEMA relief per capita is positive and statistically significant, and the R^2 is 42 percent.[8]

If we include additional lags of FEMA relief per capita in the regression, then none of the estimated coefficients is statistically significant.[9] These regressions are not reported in Leeson and Sobel (2008). However, they note that adding additional lags to the regression in column 1 "makes this specification sensitive to outliers." Our findings are consistent with this observation. Because of this sensitivity, Leeson and Sobel (2008) consider the impact of excluding the four most corrupt states from the analysis. These states are Illinois, Louisiana, Mississippi, and North Dakota, based on the PIN data for 1990–1999.

Columns 4 through 6 of table 2 report the results of the panel regressions with these four states excluded. Once again, the results are consistent with those reported in table 1 of Leeson and Sobel (2008). The estimated coefficients on the first lag of FEMA relief per capita are positive and statistically significant, as are the estimated coefficients on the second lag of FEMA relief per capita. We also report the results with Louisiana, Mississippi, North Dakota, and South Dakota excluded (columns 7 through 9), which are the four most corrupt states based on the PIN data for the full sample period, and with only Louisiana, Mississippi, and North

[8] There is a slight difference in point estimates: 0.045 here versus 0.055 in their table 1. This difference probably reflects some differences in the data sources along with the tendency for FEMA to revise the reported disaster aid figures over time.

[9] Note that the number of observations decreases each time we include an additional lag of FEMA relief per capita even though the sample period begins in 1990 and our data on disaster aid extend back to 1986. This is because we want to replicate as closely as possible the approach used by Leeson and Sobel (2008) to construct their tables.

Dakota excluded (columns 10 through 12), which appear to be outliers based on a plot of the average annual number of corruption convictions per 100,000 state residents versus the annual FEMA relief per capita (see figure 2). In each case, the results are similar to those of Leeson and Sobel (2008). Adding controls to the regressions (panel B) does not alter the statistical significance of these findings.

If we view the evidence in table 2 in isolation, then the picture that emerges is one of a statistically significant and relatively robust relationship between federal disaster aid and public corruption. We now consider the question of whether the same is true when we use the TRAC convictions series for 1990–1999 instead of the PIN series. Panel B of figure 1 provides the first hint at an answer. It plots the average annual number of corruption convictions for federal, state, and local officials per 100,000 state residents versus the total number of declared natural disasters for the state over the 1953–2008 period. The scale of this plot is the same as the scale of the plot in panel A. Although there is some suggestion of a positive relationship between the two variables, it appears to be much weaker than is suggested by the plot using PIN data in panel A. Hence, it appears that the convictions contained in the PIN data but missing from the TRAC data are not inconsequential to the analysis.

In table 3 (page 33) we reestimate the panel data regressions reported in table 2 using the TRAC corruption convictions for federal, state, and local officials per 100,000 state residents. The basic message of the results is readily apparent. None of the estimated coefficients on the lagged values of FEMA relief per capita are statistically significant. The R^2 values are uniformly lower than in table 2, and all the estimated coefficients on the first lag of FEMA relief per capita are actually negative. Because the only change going from table 2 to table 3 is the choice of convictions series, the difference in the estimated coefficients for each variable across the two tables is due solely to the differences between the PIN and TRAC data.[10]

The disparity between the two sets of results, along with the analysis of Cordis and Milyo (forthcoming), suggests that the Leeson and Sobel (2008) findings may be driven by convictions that are included in the PIN data but not in the TRAC data. As noted earlier, the evidence suggests that these are largely convictions for postal service crimes that do not fall under the usual definition of public corruption. Although destroying, stealing, or tampering with mail is a federal offense, this is not the type of offense that is typically mentioned when corruption is discussed in the scholarly literature. Because it is difficult to come up with a plausible explanation for why federal disaster aid would be causally linked to such crimes, it seems reasonable to question whether the results in table 2 are indicative of a true causal relationship.[11]

To investigate further, we extend the sample period to 1986–2008. If there is actually an underlying relationship between federal disaster aid and corruption, then increasing the number of observations, and hence the precision of our regression estimates, should tend to strengthen the empirical evidence in this regard.

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[10] In fact, the coefficient estimates obtained by specifying the difference between the PIN and TRAC convictions series as the dependent variable in the regressions are identical to those obtained by simply subtracting the estimate of the coefficient in table 3 from the corresponding estimate in table 2. Although we do not report the results of this regression, it shows that there are statistically significant differences between the results in tables 2 and 3.

[11] Although the analysis suggests that the variation in convictions for postal service crimes across states drives the regression results in table 2, we cannot draw definitive conclusions in this regard. It is possible that the inclusion of these convictions in the PIN data is innocuous in the sense that they are cross-sectionally uncorrelated with the provision of disaster aid. Of course, then the PIN convictions series would have to include convictions for some other type of offense that is both missing from the TRAC data and cross-sectionally correlated with disaster aid. Even if one views this as a plausible scenario, the fact that the TRAC and EOUSA data are in such close agreement would still raise concerns about whether the offenses in question can reasonably be classified as public corruption.

3.2. ***Results for the 1986–2008 Sample Period***

We begin by plotting the average annual number of corruption convictions per 100,000 state residents for 1986–2008 versus the annual FEMA relief per capita. Figure 2 (page 34) shows the plots obtained with the PIN convictions series. The plot in panel A is for all 50 states. We can see from this plot that Louisiana, Mississippi, and North Dakota appear to be outliers. Hence, the plot in panel B excludes these three states to provide a better picture of the bulk of the data. Although a regression line through this data has a slightly positive slope, the relationship appears to be rather tenuous.

Figure 3 (page 35) shows the plots obtained with the TRAC convictions series for federal, state, and local officials. Once again, Louisiana, Mississippi, and North Dakota appear to be outliers in the plot in panel A. When we exclude these three states to provide a better picture of the bulk of the data, the regression line through the data is essentially flat.

Turning to the panel regressions, we again find little evidence of a relationship between federal disaster aid and corruption. Table 4 (page 36) presents the results for the PIN convictions series. For completeness we show the estimates obtained using all 50 states and with the same three sets of excluded states that were considered in tables 2 and 3. Unlike for the 1990–1999 sample period, the panel regressions using the PIN data for 1986–2008 generally do not produce statistically significant estimates of the coefficients on the lagged values of FEMA relief per capita. The only exception is at the second lag for the regressions that use data for all 50 states (columns 2 and 3). In addition, the panel regressions have lower explanatory power for the 1986–2008 sample. The R^2 values in table 4 are in the 28–33 percent range, compared to a range of 35–50 percent in table 2.

In the one case in which we find statistical significance, the estimated economic magnitude of the disaster aid effect is relatively small. In table 2 the estimated coefficient on the first lag of FEMA relief per capita is 0.045 and is statistically significant at the 5 percent level. Thus the implication is that a $100 increase in FEMA relief per capita is associated with a $(\frac{0.045}{0.29}) \times 100 = 15.5\%$ increase in the corruption level for the average state in the first year after it is disbursed.[12] This is substantial. In comparison, the estimated coefficients on the second lag of FEMA relief per capita in columns 2 and 3 of table 4 are between 0.003 and 0.004. Although they are statistically significant at the 5 percent level, the implication is that a $100 increase in FEMA relief per capita is associated with about a $(\frac{0.004}{0.33}) \times 100 = 1.2\%$ increase in the corruption level for the average state in the second year after it is disbursed.

Table 5 (page 37) replicates the regressions of table 4 using the TRAC convictions series for federal, state, and local officials. The results do not support the hypothesis that disaster aid engenders corruption. Most of the estimated coefficients on the lagged values of FEMA relief per capita are negative, and of those that are positive, none is statistically significant. Moreover, there is a further decline in the R^2 values relative to those in table 2.

Overall, the analysis for the 1986–2008 sample period provides virtually no evidence for or against a relationship between federal disaster aid and corruption. In other words, the results obtained using the PIN data are not robust to the choice of sample period. This weakens the case for the Leeson and Sobel (2008) hypothesis because increasing the sample period produces more precise estimates of the regression coefficients. If there is a stable causal relationship between disaster aid and corruption, then it should become easier to detect this relationship as the sample size increases. The sensitivity of the results to the choice of sample period is therefore a concern.

[12] The mean of the PIN DOJ Convictions per Capita variable for the 1990–1999 sample period is 0.29.

3.3. *Regressions Using Only FEMA, State, and Local Convictions*

Leeson and Sobel (2008) point to a number of ways that corrupt officials can appropriate disaster aid, such as soliciting bribes for awarding reconstruction contracts, directly stealing relief resources, and indirectly transferring relief funds to private parties for personal gain. They also cite anecdotal evidence to illustrate each. Specifically, they note that after flooding in Buchanan County, Virginia, "county officials embarked on a frenzy of bribe solicitation for relief-related reconstruction contracts that ended in 16 indictments for public corruption"; that in the aftermath of a hurricane in Florida, "an employee of Florida's Department of Health and Rehabilitative Services attempted to steal $48,000 in FEMA relief"; and that following a Typhoon in Guam, "the governor of Guam's chief of staff illegally awarded the hefty contract [to replace damaged bus shelters] to the governor's primary business rival in return for the rival's support of the governor in the 1998 gubernatorial campaign."

The common theme of these anecdotes is that the corruption involves state and local officials. This is precisely what we would expect to see, given the way that the disaster aid is distributed. The federal government provides three basic categories of disaster assistance to the states: assistance for individuals and businesses, public assistance, and hazard mitigation assistance. Once a disaster declaration is issued, FEMA coordinates the efforts of other federal agencies, state and local governments, and voluntary agencies to provide disaster assistance.

The disaster aid provided by the federal government flows primarily through three federal agencies before it is distributed to the states: FEMA, the Small Business Administration (SBA), and the United States Department of Agriculture (USDA).[13] This suggests that most of the

[13] There is limited information on the flow of disaster relief funds by agency that is easily accessible. One source that provides a comprehensive snapshot is "A Descriptive Analysis of Federal Relief, Insurance, and Loss Reduction Programs for Natural Hazards," A Report Prepared Pursuant to the Request of the Subcommittee on

federal officials who work within a state should not have significant opportunities to fraudulently appropriate disaster relief funds. Although some FEMA, SBA, and USDA officials might engage in corruption, the number of federal officials who work at these agencies within a given state is relatively low. Thus any increase in federal corruption convictions associated with an inflow of disaster aid should be quite small. This view is consistent with the available empirical evidence. For example, the majority of federal disaster aid flows directly through FEMA. Nonetheless, the TRAC data reveal that, on average, fewer than two FEMA officials per year were convicted for corruption during the 1986–2008 sample period.

If the provision of federal disaster aid to a state creates new opportunities for public corruption, then these opportunities should be highly concentrated in the state and local government agencies through which the disaster aid flows. Therefore, any relationship between the amount of disaster aid that a state receives and its corruption level should show up almost exclusively in the number of state and local officials convicted for corrupt acts. To see whether such a relationship exists, we repeat the panel regressions for the 1986–2008 sample period using the TRAC convictions series that excludes convictions for all non-FEMA federal officials. We believe that these regressions provide the most straightforward and relevant test of the Leeson and Sobel (2008) hypothesis. The results of this final set of regressions are reported in table 6 (page 38).

In general, the results in table 6 look similar to those reported in table 5. Most of the estimated coefficients on the lagged values of FEMA relief per capita are negative, and none of the estimates is statistically significant. It does not matter whether we include or exclude the

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Policy Research and Insurance of the Committee on Banking, Finance and Urban Affairs, Committee Print 102-15 (Washington, DC: Congressional Research Service, October 15, 1992). Table C-1 of this report provides detailed information on federal disaster relief provided to South Carolina, North Carolina, Virginia, and Puerto Rico following the devastation caused by Hurricane Hugo in 1989. The relief provided by FEMA totaled $1.78 billion. Other federal agencies provided $0.85 billion, of which the SBA accounted for $0.45 billion and the USDA accounted for $0.09 billion.

controls, or whether we use all 50 states or only 46 states. The panel regressions produce no reliable evidence of a relationship between corruption convictions per capita and the lagged values of FEMA relief per capita. These findings extend and reinforce those obtained using convictions of officials at all levels of government.

We are not claiming, of course, to have definitively established the absence of any relationship between federal disaster aid and corruption. The anecdotal evidence recounted by Leeson and Sobel (2008) paints a vivid picture. We have no doubt that some federal aid is siphoned away by state and local officials through corrupt practices. In our view, however, the relevant empirical question is whether this channel generates an economically meaningful amount of corruption. If we cannot find clear and convincing statistical evidence of a relationship between disaster aid and corruption using more than 20 years of data, then it is natural to question the economic significance of any relationship that may in fact exist.

3.4. *Evidence from the Hurricane Katrina Relief Effort*

The federal response to the enormous devastation wrought by Hurricane Katrina in 2005 provides additional evidence on the issue of economic significance. Because the scale of the disaster was unprecedented, so was the amount of federal disaster aid provided to the affected states. More than 90 percent of the entire amount of federal disaster aid received by both Louisiana and Mississippi over the 1986–2008 sample period was provided in 2005. Leeson and Sobel (2008) highlight the potential impact of this large influx of federal dollars on the Gulf Coast region in their concluding remarks, noting that “the magnitude of Katrina-related disbursements, coupled with the results of our analysis, suggest a considerable spike in this region’s already significant corruption level.”

To see whether the data bear out this prediction, we plot both the PIN and the TRAC corruption convictions series for the years 2000–2010 for the five states that received the largest amounts of disaster aid per capita in 2005: Louisiana, Mississippi, Alabama, Florida, and Texas.[14] The results are shown in figure 4 (page 39). The plot in panel A is for the PIN conviction series. The plot in panel B is for the TRAC conviction series that includes all federal, state, and local officials. Each plot contains a vertical line at 2005 that separates the pre- and post-Katrina periods.

The convictions data are lumpy, so the lines connecting the data points display a good deal of variability through time. Nevertheless, it is apparent from these plots that the predicted spike in corruption never materialized, at least as measured by the convictions data. The average level of convictions for the pre-Katrina years across the five states is similar to that for the post-Katrina years. There is some suggestion of an increase in corruption levels for Louisiana and Alabama using the PIN conviction series, but this looks more like normal variation in the convictions data than a spike.[15] Moreover, there is no clear increase in corruption using the TRAC conviction series. The line for Louisiana is flat (so any increase in panel A seems to be tied to the inclusion of postal crimes in the PIN data), and the line for Mississippi trends downward. Only Alabama shows any indication of a potential increase in corruption. Given the extraordinary amounts of disaster aid provided to the five states in question, we regard the absence of a clear, unambiguous spike in corruption convictions for the

[14] Note that we extend these plots beyond the end of the sample period for which we have disaster aid data to allow for the possibility of a time lag between uncovering public corruption related to the federal aid provided in the wake of Katrina and prosecuting the offenders.

[15] In the case of Louisiana, for example, the mean and standard deviation of the number of convictions per 100,000 residents using the PIN data are 0.64 and 0.30 for the full pre-Katrina part of our sample period (1986–2004). All the post-Katrina data points are within plus or minus two standard deviations of the pre-Katrina mean. In addition, the maximum number of convictions per 100,000 residents for the 1986–2010 period occurs in 1990, not during the post-Katrina period.

post-Katrina period as telling evidence. In light of this evidence, and that from the regression analysis, it does not seem tenable to argue that federal disaster aid generates an economically meaningful amount of public corruption.

Figure 5 (page 40) lends additional weight to this viewpoint. It replicates the plots in figure 4 using the TRAC convictions series that excludes convictions for all non-FEMA federal officials. As emphasized in our discussion of the regression analysis, we expect any relationship between the amount of federal disaster aid that a state receives and its corruption level to show up primarily in the number of state and local officials convicted for corrupt acts. Figure 5 reveals that, not only is there no clear spike in the convictions of state and local officials in the post-Katrina period, but the average level of convictions across the five states is actually higher for the pre-Katrina period than for the post-Katrina period. It is very difficult to reconcile this finding with the existence of an economically significant causal relationship between the amount of federal disaster aid provided to a state and the amount of public corruption in the state.

3.5. *Additional Robustness Checks*

We performed a variety of additional robustness checks on our results. Some examples include dividing the corruption convictions and FEMA aid by the number of government employees in the state instead of the state population, augmenting the convictions of FEMA, state, and local officials with information on state and local convictions culled from media reports, and augmenting the convictions of FEMA, state, and local officials with convictions of SBA and USDA officials. None of these changes had any meaningful impact on our findings.

We also tried using total filings per capita instead of convictions per capita, and using only those convictions in corruption cases for which the lead charge fell under 18 U.S.C. 666

"Theft or Bribery in Programs Receiving Federal Funds." Once again, the panel regressions using these variables did not produce statistically significant estimates of the coefficients on the lagged values of FEMA relief per capita.

4. Conclusions

The proposition that bribery, theft, and political payoffs associated with an influx of federal disaster aid are significant contributing factors to the geographic patterns of public corruption in the United States is intriguing. Although this proposition finds substantial support in the analysis of Leeson and Sobel (2008), a closer look at the empirical evidence produces a murkier picture. Evidence of a positive and statistically significant relationship between annual FEMA relief per capita and the annual number of corruption convictions per capita is largely confined to Leeson and Sobel's 1990–1999 sample and may be driven by convictions recorded in the PIN data that are for crimes committed by postal service employees, such as stealing mail. Using an alternative convictions series that considers only the public officials who are most likely to have the opportunity to fraudulently appropriate federal disaster aid, we find no reliable evidence for or against an underlying causal relationship between disaster aid and corruption.

Two key conclusions follow our investigation. First, our findings do not support the view that public corruption could potentially be reduced by revamping the disaster aid process. Although we cannot claim to have definitively established the absence of any relationship between federal disaster aid and corruption, we believe our findings raise doubts about the economic significance of any relationship that exists. Accordingly, policymakers should question whether anticorruption efforts should therefore be directed at other areas in which there is convincing evidence that these efforts can have an effect.

Second, our findings raise a range of questions about the PIN data that have been used so extensively in the corruption literature. If the evidence of a relationship between federal disaster aid and corruption for the 1990–1999 sample period is driven by the inclusion of convictions for postal service crimes in the PIN data, then this raises the real possibility that other findings in the literature might be sensitive to the presence of these convictions as well. Future research should place more emphasis on assessing the impact of such data issues.

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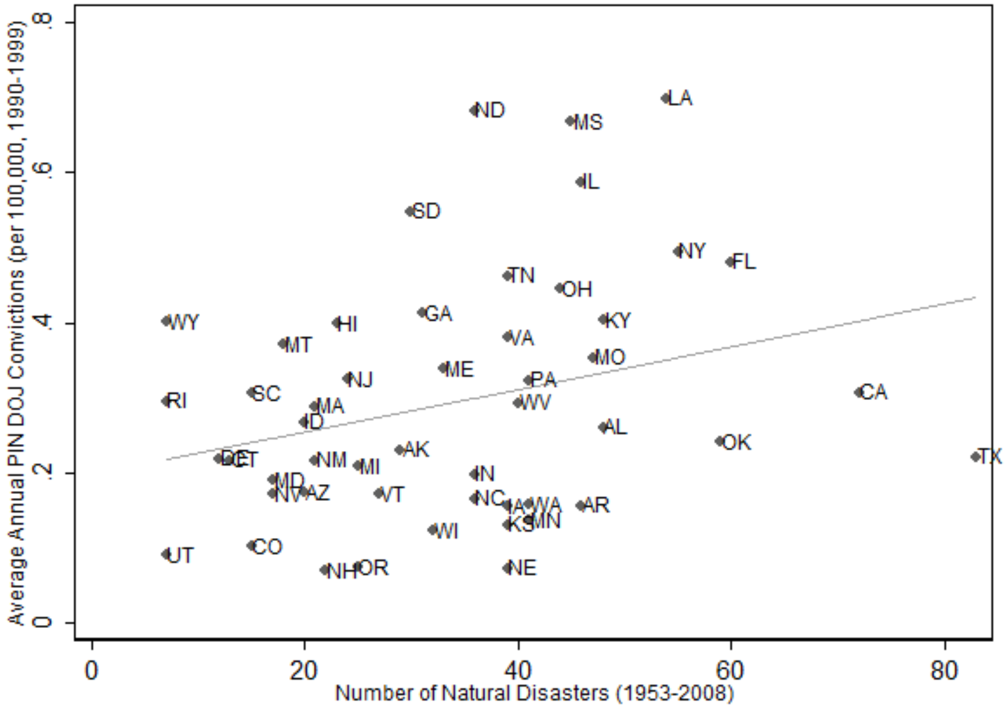
Table 1. Descriptive Statistics

Variable	Mean	Standard deviation	Minimum	Maximum
PIN DOJ Convictions per Capita	0.33	0.31	0.00	2.55
TRAC Convictions per Capita	0.18	0.21	0.00	2.53
State, Local & FEMA Conv. per Capita	0.07	0.14	0.00	1.90
FEMA Relief per Capita	0.20	2.33	0.00	68.09
Population Inverse	0.49	0.50	0.03	2.20
Log Per Capita Income	10.42	0.18	9.92	10.98
Share Government Employees	5.78	1.98	3.02	14.26

Notes: Descriptive statistics are for the 1986–2008 sample (N = 1,150). PIN DOJ Convictions per Capita is the number of corruption convictions from the Public Integrity Section of the Department of Justice per 100,000 residents. TRAC Convictions per Capita is the number of corruption convictions of federal, state, and local officials from the Transactional Records Access Clearinghouse (TRAC) database per 100,000 residents. State, Local & FEMA Conv. per Capita is the number of corruption convictions of state, local, and FEMA officials from the TRAC database per 100,000 residents. FEMA Relief per Capita represents hundreds of constant 2010 dollars of Federal Emergency Management Agency relief per capita. Population Inverse is one divided by population (in millions). Log Per Capita Income is the log of real per capita income. Share Government Employees is the percentage of the state workforce employed by the federal and state governments. FEMA data are from the Public Entity Risk Institute. Population and income data are from the US Census. Government employment data are from the Bureau of Labor Statistics.

Figure 1. Corruption and Natural Disasters, 1990–1999

Panel A: PIN DOJ Convictions



Panel B: TRAC Convictions

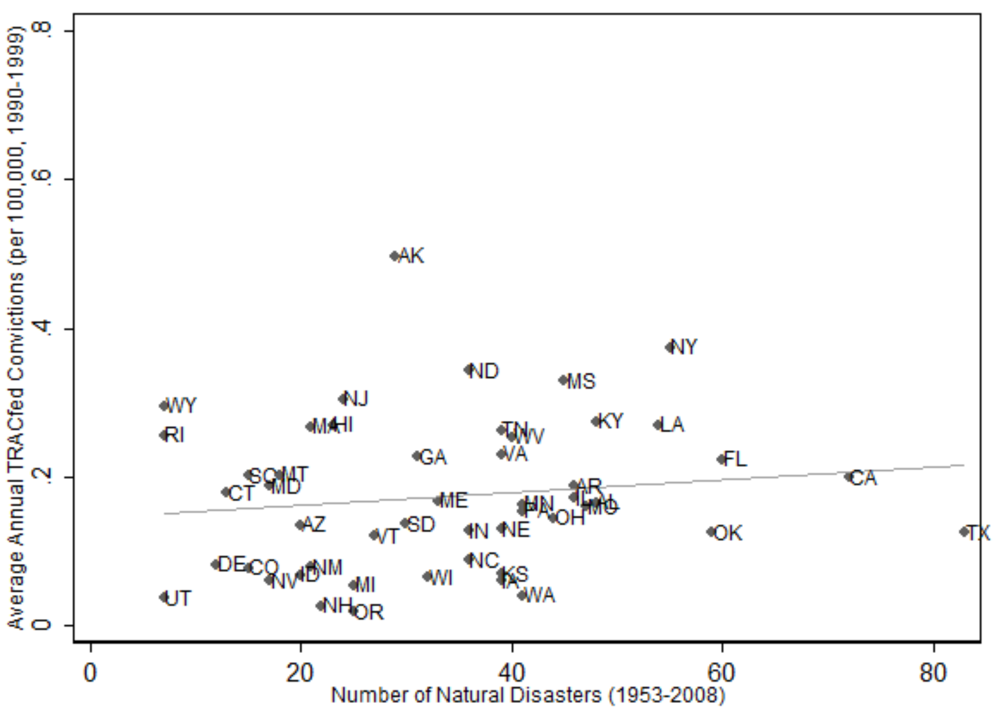


Table 2. Corruption and FEMA Relief, PIN DOJ Convictions per 100,000 Residents, 1990–1999

	All states			Excluding LA, MS, ND, IL			Excluding LA, MS, ND, SD			Excluding LA, MS, ND		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. No controls												
FEMA, $t-1$	0.045**	0.035	0.026	0.060*	0.065*	0.068*	0.042	0.052*	0.057*	0.059*	0.064*	0.067*
	(0.014)	(0.018)	(0.022)	(0.026)	(0.024)	(0.026)	(0.022)	(0.023)	(0.025)	(0.026)	(0.024)	(0.026)
FEMA, $t-2$		−0.039	−0.048		0.071**	0.078**		0.077**	0.084**		0.072**	0.078**
		(0.046)	(0.050)		(0.023)	(0.025)		(0.022)	(0.024)		(0.023)	(0.025)
FEMA, $t-3$			0.014			0.065			0.053			0.064
			(0.034)			(0.032)			(0.029)			(0.032)
R^2	0.42	0.47	0.50	0.35	0.40	0.43	0.39	0.45	0.48	0.38	0.44	0.46
N	450	400	350	414	368	322	414	368	322	423	376	329
B. With controls												
FEMA, $t-1$	0.051**	0.043*	0.031	0.069*	0.078**	0.080*	0.052*	0.065*	0.067*	0.067*	0.077**	0.078*
	(0.014)	(0.020)	(0.024)	(0.027)	(0.028)	(0.032)	(0.023)	(0.026)	(0.031)	(0.027)	(0.028)	(0.032)
FEMA, $t-2$		−0.035	−0.044		0.077**	0.084*		0.083**	0.090**		0.077**	0.084*
		(0.047)	(0.050)		(0.028)	(0.032)		(0.027)	(0.030)		(0.029)	(0.032)
FEMA, $t-3$			0.020			0.072			0.060			0.071
			(0.034)			(0.037)			(0.033)			(0.037)
R^2	0.43	0.48	0.50	0.37	0.42	0.44	0.41	0.47	0.48	0.39	0.45	0.47
N	450	400	350	414	368	322	414	368	322	423	376	329

* and ** denote estimated statistical significance at the 5 and 1 percent levels, respectively.

Notes: Both panels present the results of OLS regressions with state and year-fixed effects. Standard errors, in parentheses, are clustered by state. Columns 4, 5, and 6 exclude Louisiana, Mississippi, North Dakota, and Illinois. Columns 7, 8, and 9 exclude Louisiana, Mississippi, North Dakota, and South Dakota. Columns 10, 11, and 12 exclude Louisiana, Mississippi, and North Dakota. PIN DOJ Convictions per 100,000 Residents is the number of corruption convictions from the Public Integrity Section of the Department of Justice per 100,000 residents. FEMA, $t-1$; FEMA, $t-2$; and FEMA, $t-3$ are lagged FEMA relief per capita variables for one, two, and three years. Panel B includes the following controls: the population inverse, the log of income per capita, and the percentage of the workforce employed by the federal and state governments.

Table 3. Corruption and FEMA Relief, TRAC Convictions per 100,000 Residents, 1990–1999

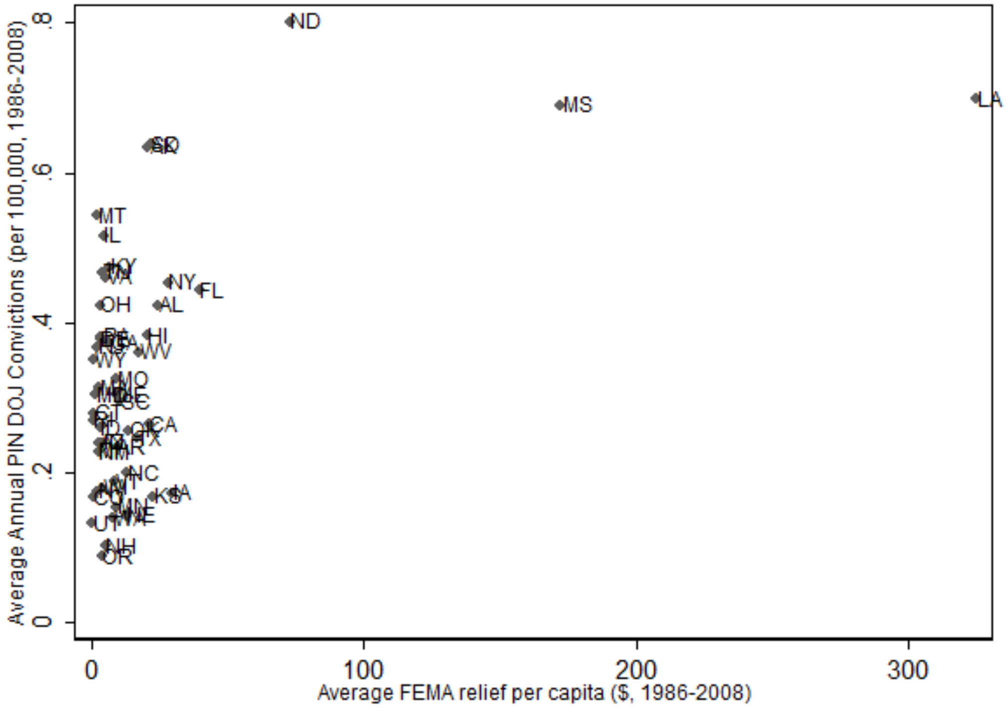
	All states			Excluding LA, MS, ND, IL			Excluding LA, MS, ND, SD			Excluding LA, MS, ND		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. No controls												
FEMA, $t-1$	−0.012	−0.013	−0.015	−0.045	−0.036	−0.038	−0.040	−0.034	−0.034	−0.046	−0.036	−0.038
	(0.017)	(0.013)	(0.013)	(0.028)	(0.023)	(0.022)	(0.030)	(0.024)	(0.024)	(0.028)	(0.022)	(0.022)
FEMA, $t-2$		0.009	0.007		0.071	0.070		0.069	0.072		0.070	0.070
		(0.032)	(0.033)		(0.054)	(0.058)		(0.057)	(0.061)		(0.054)	(0.058)
FEMA, $t-3$			−0.006			0.008			0.012			0.010
			(0.022)			(0.021)			(0.020)			(0.022)
R^2	0.31	0.35	0.35	0.31	0.37	0.37	0.32	0.38	0.38	0.31	0.36	0.37
N	450	400	350	414	368	322	414	368	322	423	376	329
B. With controls												
FEMA, $t-1$	−0.010	−0.013	−0.015	−0.045	−0.041	−0.044	−0.039	−0.038	−0.037	−0.045	−0.041	−0.043
	(0.017)	(0.015)	(0.017)	(0.030)	(0.026)	(0.031)	(0.031)	(0.027)	(0.033)	(0.029)	(0.025)	(0.031)
FEMA, $t-2$		0.010	0.008		0.067	0.066		0.067	0.069		0.067	0.067
		(0.030)	(0.031)		(0.051)	(0.053)		(0.054)	(0.056)		(0.051)	(0.054)
FEMA, $t-3$			−0.006			0.005			0.011			0.007
			(0.019)			(0.018)			(0.017)			(0.019)
R^2	0.31	0.36	0.35	0.31	0.38	0.37	0.32	0.39	0.38	0.31	0.37	0.37
N	450	400	350	414	368	322	414	368	322	423	376	329

* and ** denote estimated statistical significance at the 5 and 1 percent levels, respectively.

Notes: Both panels present the results of OLS regressions with state and year fixed effects. Standard errors, in parentheses, are clustered by state. Columns 4, 5, and 6 exclude Louisiana, Mississippi, North Dakota, and Illinois. Columns 7, 8, and 9 exclude Louisiana, Mississippi, North Dakota, and South Dakota. Columns 10, 11, and 12 exclude Louisiana, Mississippi, and North Dakota. TRAC Convictions per 100,000 Residents is the number of corruption convictions of federal, state, and local officials from the Transactional Records Access Clearinghouse database per 100,000 residents. FEMA, $t-1$; FEMA, $t-2$; and FEMA, $t-3$ are lagged FEMA relief per capita variables for one, two, and three years. Panel B includes the following controls: the population inverse, the log of income per capita, and the percentage of the workforce employed by the federal and state governments.

Figure 2. Corruption and FEMA Relief, PIN DOJ Convictions, 1986–2008

Panel A: All States



Panel B: Excluding ND, MS, LA

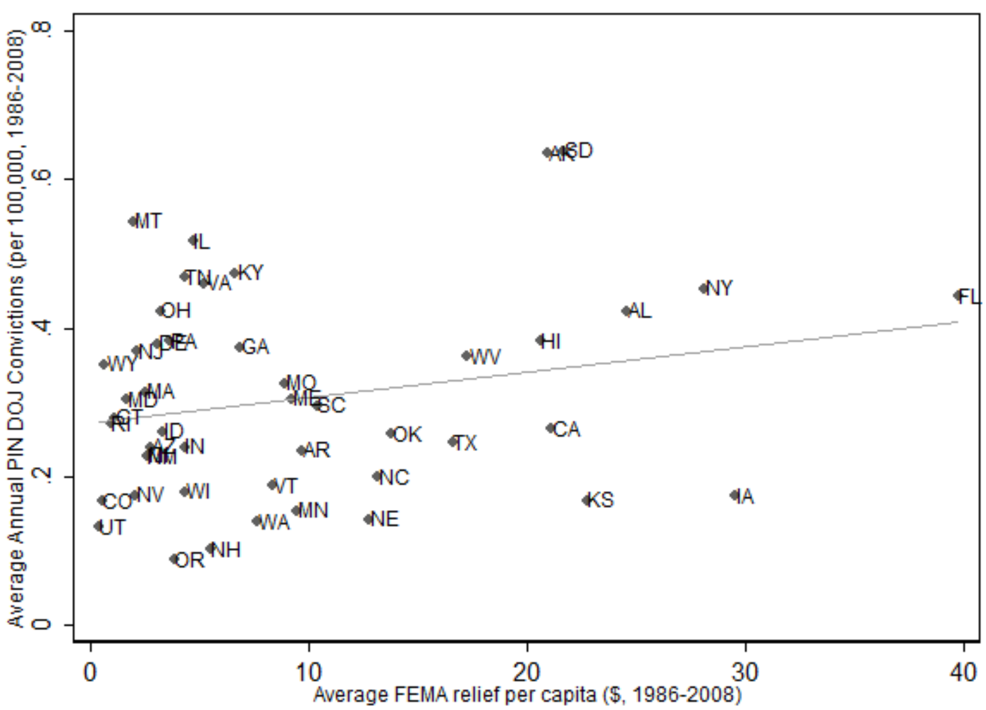
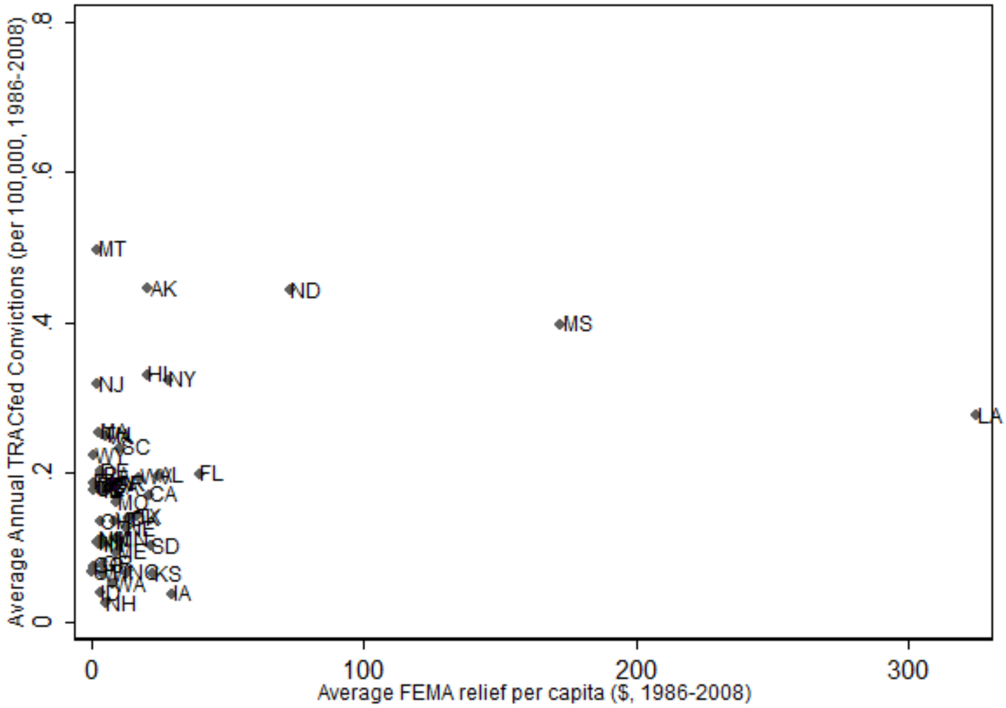


Figure 3. Corruption and FEMA Relief, TRAC Convictions, 1986–2008

Panel A: All States



Panel B: Excluding ND, MS, LA

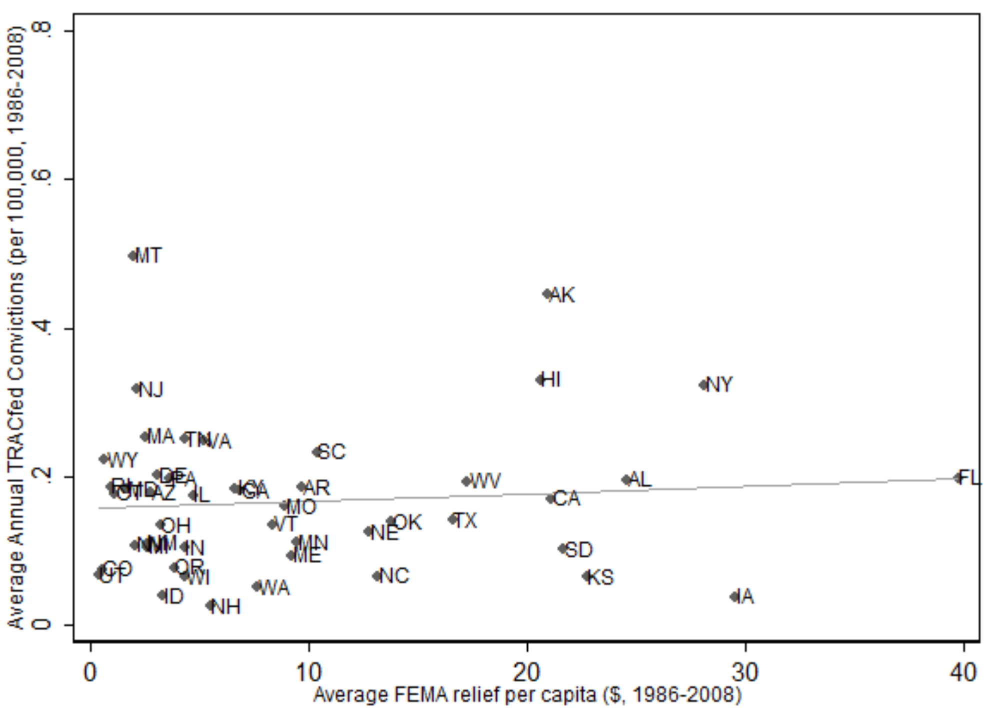


Table 4. Corruption and FEMA Relief, PIN DOJ Convictions per 100,000 Residents, 1986–2008

	All states			Excluding LA, MS, ND, IL			Excluding LA, MS, ND, SD			Excluding LA, MS, ND		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. No controls												
FEMA, $t-1$	0.003	0.003	0.003	0.024	0.023	0.024	0.020	0.019	0.021	0.025	0.024	0.026
	(0.005)	(0.005)	(0.005)	(0.025)	(0.024)	(0.025)	(0.025)	(0.024)	(0.025)	(0.025)	(0.024)	(0.025)
FEMA, $t-2$		0.003*	0.004*		0.023	0.021		0.030	0.029		0.025	0.023
		(0.001)	(0.001)		(0.033)	(0.032)		(0.034)	(0.032)		(0.033)	(0.032)
FEMA, $t-3$			0.001			0.025			0.030			0.027
			(0.002)			(0.021)			(0.022)			(0.021)
R^2	0.33	0.33	0.33	0.28	0.28	0.28	0.28	0.28	0.28	0.29	0.29	0.29
N	1,150	1,150	1,150	1,058	1,058	1,058	1,058	1,058	1,058	1,081	1,081	1,081
B. With controls												
FEMA, $t-1$	0.003	0.003	0.003	0.027	0.026	0.028	0.023	0.022	0.024	0.029	0.028	0.029
	(0.005)	(0.005)	(0.005)	(0.026)	(0.025)	(0.025)	(0.025)	(0.024)	(0.025)	(0.026)	(0.025)	(0.025)
FEMA, $t-2$		0.004*	0.004*		0.024	0.023		0.031	0.030		0.026	0.025
		(0.002)	(0.002)		(0.033)	(0.032)		(0.034)	(0.033)		(0.033)	(0.032)
FEMA, $t-3$			0.001			0.027			0.031			0.028
			(0.002)			(0.021)			(0.022)			(0.021)
R^2	0.33	0.33	0.33	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.30
N	1,150	1,150	1,150	1,058	1,058	1,058	1,058	1,058	1,058	1,081	1,081	1,081

* and ** denote estimated statistical significance at the 5 and 1 percent levels, respectively.

Notes: Both panels present the results of OLS regressions with state and year fixed effects. Standard errors, in parentheses, are clustered by state. Columns 4, 5, and 6 exclude Louisiana, Mississippi, North Dakota, and Illinois. Columns 7, 8, and 9 exclude Louisiana, Mississippi, North Dakota, and South Dakota. Columns 10, 11, and 12 exclude Louisiana, Mississippi, and North Dakota. PIN DOJ Convictions per 100,000 Residents is the number of corruption convictions from the Public Integrity Section of the Department of Justice per 100,000 residents. FEMA, $t-1$; FEMA, $t-2$; and FEMA, $t-3$ are lagged FEMA relief per capita variables for one, two, and three years. Panel B includes the following controls: the population inverse, the log of income per capita, and the percentage of the workforce employed by the federal and state governments.

Table 5. Corruption and FEMA Relief, TRAC Convictions per 100,000 Residents, 1986–2008

	All states			Excluding LA, MS, ND, IL			Excluding LA, MS, ND, SD			Excluding LA, MS, ND		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. No controls												
FEMA, t−1	−0.000	−0.000	−0.000	−0.016	−0.017	−0.017	−0.015	−0.016	−0.016	−0.016	−0.017	−0.017
	(0.003)	(0.003)	(0.003)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
FEMA, t−2		−0.001	−0.001		0.022	0.022		0.020	0.020		0.021	0.021
		(0.001)	(0.001)		(0.028)	(0.027)		(0.028)	(0.028)		(0.028)	(0.027)
FEMA, t−3			0.000			−0.001			0.001			−0.000
			(0.001)			(0.020)			(0.021)			(0.020)
R^2	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
N	1,150	1,150	1,150	1,058	1,058	1,058	1,058	1,058	1,058	1,081	1,081	1,081
B. With controls												
FEMA, t−1	−0.001	−0.001	−0.001	−0.016	−0.017	−0.017	−0.016	−0.017	−0.016	−0.017	−0.017	−0.017
	(0.003)	(0.003)	(0.003)	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)
FEMA, t−2		−0.002	−0.002		0.022	0.022		0.020	0.020		0.022	0.022
		(0.001)	(0.001)		(0.027)	(0.026)		(0.027)	(0.026)		(0.027)	(0.026)
FEMA, t−3			−0.001			−0.001			0.002			−0.000
			(0.002)			(0.020)			(0.020)			(0.020)
R^2	0.29	0.29	0.29	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28	0.28
N	1,150	1,150	1,150	1,058	1,058	1,058	1,058	1,058	1,058	1,081	1,081	1,081

* and ** denote estimated statistical significance at the 5 and 1 percent levels, respectively.

Notes: Both panels present the results of OLS regressions with state and year fixed effects. Standard errors, in parentheses, are clustered by state. Columns 4, 5, and 6 exclude Louisiana, Mississippi, North Dakota, and Illinois. Columns 7, 8, and 9 exclude Louisiana, Mississippi, North Dakota, and South Dakota. Columns 10, 11, and 12 exclude Louisiana, Mississippi, and North Dakota. TRAC Convictions per 100,000 Residents is the number of corruption convictions of federal, state, and local officials from the Transactional Records Access Clearinghouse database per 100,000 residents. FEMA, t−1; FEMA, t−2; and FEMA, t−3 are lagged FEMA relief per capita variables for one, two, and three years. Panel B includes the following controls: the population inverse, the log of income per capita, and the percentage of the workforce employed by the federal and state governments.

Table 6. Corruption and FEMA Relief, Convictions of State, Local, and FEMA Officials per 100,000 Residents, 1986–2008

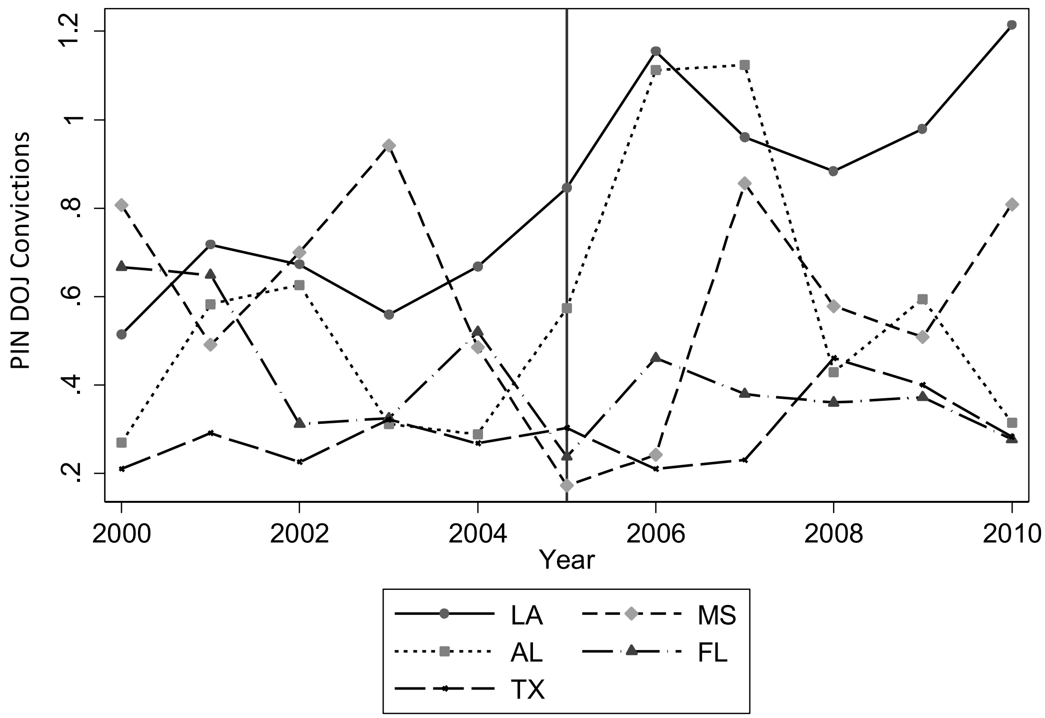
	All states			Excluding LA, MS, ND, IL			Excluding LA, MS, ND, SD			Excluding LA, MS, ND		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. No controls												
FEMA, $t-1$	−0.001	−0.001	−0.001	−0.006	−0.006	−0.007	−0.007	−0.007	−0.007	−0.006	−0.007	−0.007
	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
FEMA, $t-2$		−0.001	−0.001		0.012	0.012		0.011	0.011		0.011	0.011
		(0.001)	(0.001)		(0.010)	(0.010)		(0.010)	(0.010)		(0.010)	(0.010)
FEMA, $t-3$			0.000			−0.001			−0.001			−0.000
			(0.001)			(0.007)			(0.007)			(0.007)
R^2	0.28	0.28	0.28	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
N	1,150	1,150	1,150	1,058	1,058	1,058	1,058	1,058	1,058	1,081	1,081	1,081
B. With controls												
FEMA, $t-1$	−0.001	−0.001	−0.001	−0.005	−0.005	−0.005	−0.006	−0.006	−0.006	−0.005	−0.006	−0.006
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
FEMA, $t-2$		−0.001	−0.001		0.012	0.012		0.011	0.011		0.012	0.012
		(0.001)	(0.001)		(0.010)	(0.010)		(0.010)	(0.010)		(0.010)	(0.010)
FEMA, $t-3$			−0.000			−0.001			−0.000			−0.000
			(0.002)			(0.006)			(0.007)			(0.006)
R^2	0.28	0.28	0.28	0.31	0.31	0.31	0.30	0.30	0.30	0.31	0.31	0.31
N	1,150	1,150	1,150	1,058	1,058	1,058	1,058	1,058	1,058	1,081	1,081	1,081

* and ** denote estimated statistical significance at the 5 and 1 percent levels, respectively.

Notes: Both panels present the results of OLS regressions with state and year fixed effects. Standard errors, in parentheses, are clustered by state. Columns 4, 5, and 6 exclude Louisiana, Mississippi, North Dakota, and Illinois. Columns 7, 8, and 9 exclude Louisiana, Mississippi, North Dakota, and South Dakota. Columns 10, 11, and 12 exclude Louisiana, Mississippi, and North Dakota. Convictions of State, Local, and FEMA Officials per 100,000 Residents is the number of corruption convictions of state, local and FEMA officials from the Transactional Records Access Clearinghouse database per 100,000 residents. FEMA, $t-1$; FEMA, $t-2$; and FEMA, $t-3$ are lagged FEMA relief per capita variables for one, two, and three years. Panel B includes the following controls: the population inverse, the log of income per capita, and the percentage of the workforce employed by the federal and state governments.

Figure 4. Pre- and Post-Katrina Convictions for Five Gulf States

Panel A: PIN DOJ Convictions (per 100,000 Residents)



Panel B: TRAC Convictions of Federal, State and Local Officials
(per 100,000 Residents)

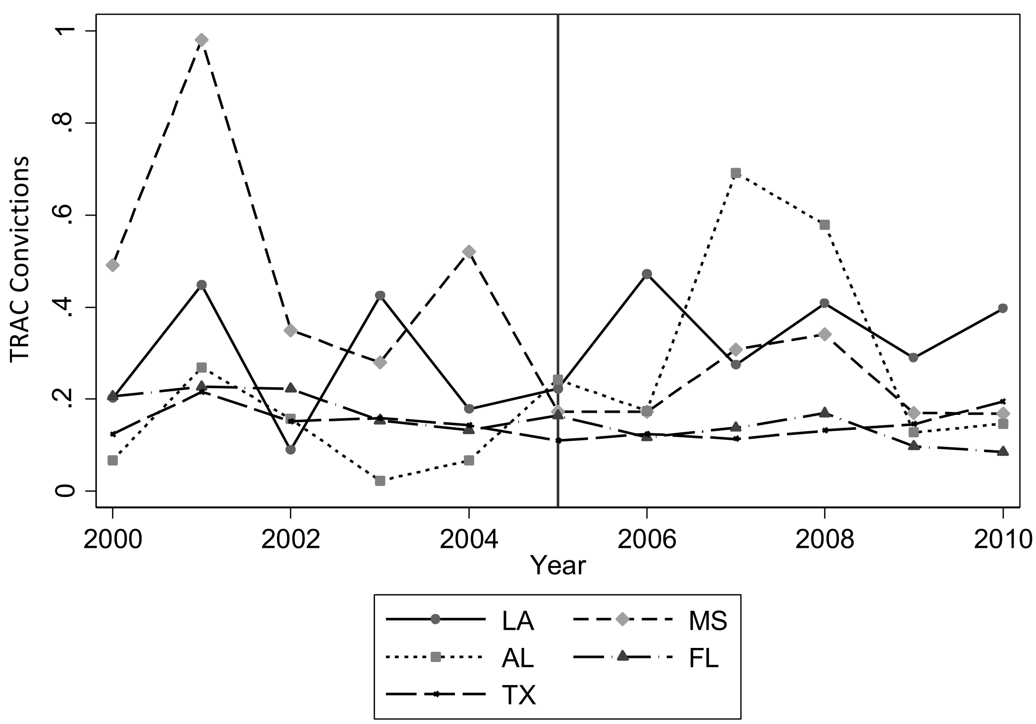


Figure 5. Pre- and Post-Katrina TRAC Convictions, Excluding Non-FEMA Federal Officials (per 100,000 Residents)