# THE EFFECT OF INSPECTOR GROUP SIZE AND FAMILIARITY ON ENFORCEMENT: EVIDENCE FROM OFFSHORE OIL PLATFORMS

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This paper examines how the behavior of inspectors changes in a group setting and by familiarity with the regulated entity. We estimate an inspector group size effect on enforcement and deterrence using variation in helicopter flying conditions as an instrumental variable for the number of inspectors that are sent to offshore oil and gas platforms. We find that an additional inspector results in an increase in the number of severe sanctions that are issued. Using the closure of an inspections office, which resulted in a reduction of prior inspections to the same platform, we find that decreasing familiarity also results in more severe sanctions being issued. Although sanction severity increases, we do not find a decrease in incidents, such as oil spills and injuries, reported by the operator in the subsequent period.

Keywords: inspections, enforcement, offshore oil, environment

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## 1. INTRODUCTION

Following Becker's [1968] seminal paper on the economics of crime and punishment, a burgeoning literature has developed extending and testing his model in both the street crime and regulatory context (see Polinsky and Shavell [2000] for a review). Much of the empirical economics of crime literature has focused on the incentives and behavior of *potential offenders*. Examples include the deterrent effect of increasing detection probability, such as by increasing police on the street [Corman and Mocan, 2000, Di Tella and Schargrodsky, 2004], referees on a court [McCormick and Tollison, 1984] or inspections of polluting plants [Magat and Viscusi, 1990, Laplante and Rilstone, 1996, Earnhart, 2004]. Other examples include the deterrent effect of increasing sanctions, such as imprisonment [Drago et al., 2009, Levitt, 1998] or fines [Shimshack and Ward, 2005]. A smaller, but growing literature has focused on the incentives and behavior of the *enforcement agent*. Recent anecdotes of industry pressure (or even "capture") of inspectors in the nuclear, coal mining, and oil drilling industries highlight the importance of understanding the role that inspectors play in ensuring compliance.

Becker and Stigler [1974] first analyzed the issue of enforcers who might not have social welfare maximization as their guiding principle. In particular, they noted that both criminal and regulatory offenders who face punishment for their violations have an incentive to influence the police officer or regulatory enforcement agency. Corruption among both police and regulatory enforcement agents is well documented [Rose-Ackerman, 1999]. Formal extensions to the Becker-Stigler model by Mookherjee and Png [1995] and Bowles and Garoupa [1997] have further examined trade-offs between detection probability, sanctions and optimal enforcer compensation. While these formal models assume monetary payoffs (e.g., bribery and corruption), influence may take on more subtle forms of persuasion. A few empirical studies have examined these nonmonetary influences. Makkai and Braithwaite [1992] studied nursing home inspectors and found that those who self-identified with the industry on an attitudinal survey were more likely to issue positive compliance ratings during an inspection. Garicano et al. [2005] empirically demonstrate bias by soccer referees who are presumably under social pressure to favor home teams. And Jin and Lee [2011] find evidence of collusive behavior between inspectors and restaurants.

To our knowledge, all of the previous studies of collusive behavior and social pressure on enforcers are based on individual behavior—not group behavior. Yet, enforcement agencies often send teams of enforcers. In fact, teams (instead of individuals) are often sent with the express goal of minimizing corruption [Klitgaard, 1988].[1] Though there are various effects that might arise by sending a group. For example, teams may be more productive than individuals [Hamilton et al., 2003], or less productive in the case of free-riding [Alchian and Demsetz, 1972]. Peer pressure within the group might influence members of the team to conform to the group norm [Kandel and Lazear, 1992]. The group norm may vary by the attitude of the inspector towards the regulated party, which then might affect their approach to enforcement. For example, Bernhard et al. [2006] and Chen and Li [2009] find that individuals are more likely to punish violators when those violations occur by an "outgroup" member as opposed to an "ingroup" member. To the extent a group of inspectors identify with the regulated party, they might be less inclined to punish a violator than a group of inspectors without such a strong identification.

We provide new insights into the productivity of teams and the inspector-offender relationship by examining data on inspections of offshore production facilities in the Gulf of Mexico. In this paper we investigate two related topics. First, what is the effect of an additional inspector on enforcement and deterrence? And what are the impacts from reducing

[1] A related literature has examined how varying the size of inspector groups has an impact on detected violations. For example, McCormick and Tollison [1984] examine the impact of increasing the number of basketball referees from two to three—and show that the accuracy of officiating improves and deters violators. Levitt [2002] found no evidence that increasing the number of NHL referees changed the number of observed infractions leading to a penalty. These studies have focused on whether groups offer more accurate assessments and their deterrent effects, and are not focused on the behavior of the enforcer and their relationship with the offender.

enforcer-offender familiarity?

Important limitations to investigating the effect of an additional inspector are endogeneity and selection bias. Platforms that are thought to be poor performers may be sent more inspectors (in anticipation of more violations) or fewer inspectors (in anticipation that violations will be easy to detect). We use weather as an instrumental variable for the number of inspectors to identify a causal effect of group size on the level of enforcement. Inspections of offshore oil and gas platforms require the use of helicopters to take inspectors to production platforms; however, whether a helicopter can fly depends on weather conditions. When helicopters are restricted to certain areas of the Gulf because of bad weather, inspection plans must be modified, and more inspectors are sent on fewer inspections.[2] We find that when an inspection on the margin of having an additional inspector is indeed given an additional inspector, the inspection is likely to result in a more stringent enforcement action. Furthermore, increasing the number of inspectors results in an increased number of severe sanctions, implying that enforcement would be increased by adding manpower to inspections. That we only find a statistically significant increase in the severe sanctions suggests that the additional inspector provides more than only an extra pair of eyes.

To further understand why an additional inspector matters, we test for evidence of regulatory capture. A key advantage of the dataset is that it provides a record of each inspector's inspection history, which allows us to calculate proxies for the familiarity an inspector has with a facility. We examine whether the enforcement actions are affected by the frequency with which an inspector has visited the platform before. It is the case that repeat inspections are driven by factors correlated with the outcome of interest (such as poor performers having more inspections in the past and therefore also more repeat visits by the same inspector). Therefore, we exploit the closure of an inspections office that resulted in some platforms being inspected by less familiar inspectors using a difference-in-difference framework. It could

[2]We first learned this through a communication with a lead inspector, but it is also borne out in the data.

be the case that inspectors more familiar with a platform would be better apt at finding violations, however we find the opposite to be true. Consistent with the hypothesis of regulatory capture, we find that decreasing the familiarity between inspectors and the regulated entity results in more stringent sanctions being imposed.

The variation in wind speed and the closure of an inspections office provide exogenous variation in inspection intensity that can then be used to examine the effect on deterring unfavorable outcomes, such as oil spills, explosions, injuries and fatalities. We use data on company-reported incidents to examine the effect inspector group size has on the frequency of oil spills and other serious accidents reported by the operator. However, we find no evidence that using more inspectors has an effect on reducing the occurrence of reported incidents in the very short term (three to nine months). Weighed down by few observations, we are unable to disentangle the likelihood that an incident is reported from the likelihood that an incident occurs, nor the effect of repeat inspections.

## 2. BACKGROUND ON INSPECTIONS IN THE GULF OF MEXICO

Inspecting offshore oil and gas platforms (facilities) is a costly endeavor. In 2010, the budget of the United States Bureau of Ocean Energy Management, Regulation and Enforcement (BOEMRE) for inspections was $23 million.[3] However, there are over 3,000 offshore production platforms in the Gulf of Mexico alone, which must be inspected at least once every year.[4] As of 2011, these inspections were carried out by a staff of only approximately 55 inspectors who had other duties including inspecting pipelines, drilling rigs, and meters recording production for royalty payments.

Moreover, there is anecdotal evidence that this limited enforcement staff was subject to industry pressure. For example, after the BP Deepwater Horizon oil spill, an internal gov-

[3]BOEMRE was formerly the Minerals Management Service (MMS), which was renamed on June 21, 2010; thus most of the data analyzed in this paper was for compliance inspections while the agency was called MMS. On October 1, 2011, BOEMRE was split into two agencies, with the newly titled Bureau of Safety and Environmental Enforcement (BSEE) having responsibility for compliance inspections.

[4]Outer Continental Shelf Lands Act of 1953 (as amended).

ernment investigation noted that inspectors in the Gulf of Mexico had been offered gifts and employment opportunities by the regulated industry [Office of Inspector General, Department of the Interior]. We do not have information on an inspector's employment (before or after being an inspector) and so are not able to examine whether "career concerns" are the cause of capture. But capture could be driven by a more subtle form of pressure. For example, according to a post-BP Deepwater Horizon investigation by the Office of Inspector General, Department of the Interior [2010]:

*One inspector reported arriving at a facility where his brother, who worked for the operator elsewhere, was flown to the facility to act as the compliance officer. The inspector informed the company that he could not conduct the inspection with his brother present. Another person worked with the inspector that day. Some inspectors told us that industry often exerts pressure on inspectors to minimize reporting violations during inspections. For example, facility personnel may make comments, such as "there goes my bonus" or "my wife is sick, and I'll lose my job," to deter inspectors from issuing violations.*

Since the BP Deepwater Horizon spill, there have been calls for significant increases in BOEMRE's budget and stepped up government enforcement activity. The 2012 fiscal year budget for BOEMRE doubled to $500 million, with the call to "hire new oil and gas inspectors."[5] An increase in the number of inspectors will likely result in an increase in the frequency of inspections, but it could also allow for an increase in the number of inspectors that are sent to each platform. In June 2011, BOEMRE announced that it began to routinely send inspection teams instead of individual inspectors to offshore oil and gas facilities as they hired more inspectors.[6]

The primary goal of inspections is to verify that platforms are being operated in a safe manner according to all laws and regulations listed in the National Possible Incident of Non-

[5] Budget of the United States Government, Fiscal Year 2012, p. 101.

[6] "BOEMRE Strengthens Offshore Inspection Program," Press Release, June 13, 2011, available at: http://www.boemre.gov/ooc/press/2011/press0613.htm

Compliance (PINC) list. Production inspections are required for all production platforms at least once annually for compliance with safety regulations, accurate recordkeeping, and proper maintenance. In fiscal year 2009, there were 614 drilling inspections, 3,862 production inspections, 296 workover and completion inspections, 7,201 meter inspections, 63 abandonment inspections, and 4,765 pipeline inspections in the Gulf of Mexico.[7] This study analyzes production inspections.[8]

An inspection group can range from one to six inspectors. A typical inspection unfolds in the following way: in approaching the platform with a helicopter, the inspector looks at the surrounding water for pollution, any drilling, or vent gas [Offshore Energy and Minerals Management, 2009]. Upon landing, the inspector walks around the platform to check its general condition, while reviewing the PINC list to determine if violations have occurred. After the walk-around, the inspector starts the paperwork review, and determines the operating ranges and safety device set points. If there is more than one inspector in the group, one inspector reviews paperwork while any other inspectors will begin testing safety devices with the operator. The operator tests the devices while the inspector verifies that the safety device is “set” within the allowable range, and “trips” at the set point or within the correct tolerance of the set point.

General violations and specific safety equipment failures are given “Incidents of Noncompliance” (INCs). There are three different types of INCs: (1) a warning (W), in which the operator is ordered to address the problem; (2) a component shut-in (C), requiring the operator to suspend the operation of a piece of equipment that is not functioning properly, which may or may not hinder production; and (3) a facility shut-in (F), which requires cessation of all production on the platform until the problem is mitigated and verified during a follow-up inspection. In addition, INCs can be referred for a civil penalty review. Any violations are written on the inspection form, and the INCs are written and given to the

[7] http://www.gomr.boemre.gov/homepg/regulate/regs/laws/enforc.html

[8] Although we use data from all inspections in constructing variables on the inspection history of inspectors.

company representative, who reads the INC and is asked if he or she has any questions. The company representative signs the INC sheet and is told to return a copy within 14 days. The inspector then returns to the district office. The lead inspector verifies the data. The file clerk forwards completed inspections to the supervisory inspector for his or her review. If a company contests the INC, the supervisory inspector may rescind the INC.

Enforcement actions taken by BOEMRE inspectors may be more than simple slaps on the wrist. Indeed, BOEMRE estimates that a facility shut-in costs a large production platform over $900,000 a day.[9] While the bulk of enforcement actions result in the less severe INCs, warnings and component shut-ins, about 2.4% of all production inspections result in a facility shut-in—amounting to millions of dollars annually in costs to the industry [Muehlenbachs et al., 2011].

## 3. WEATHER'S EFFECT ON INSPECTIONS AND GROUP SIZE

Since the inspection of offshore production platforms relies upon the ability of helicopters to transport inspectors to and from offshore platforms, weather conditions may disrupt normal inspection schedules. On average, bad weather results in inspectors only being able to fly 80% of the time [Offshore Energy and Minerals Management, 2009]. However, there are also occasions where bad weather does not completely ground flights, but instead alters the number of inspections performed and the number of inspectors sent on an inspection. Since the platforms to be inspected are determined before weather conditions are known, if there is bad weather restricting the flights to one area of the district, inspectors will be "doubled up" [personal communication with a lead inspector]. This occurs because the day's inspections are decided at the inspections office, before the inspectors leave for the airport.

We expect that the larger the geographical area, the more likely it is for weather to have an effect on group size. The larger the area, the more likely it is for there to be enough variation in wind speed that some of the planned inspections of the day would not be feasible, while

[9] http://www.noia.org/website/download.asp?id=40069

some would be. The Lake Jackson district became the district with the most dispersed platforms in the Gulf of Mexico after the inspections office in Corpus Christi was closed and subsumed by the Lake Jackson office. After October 1, 2003, all inspections for both Corpus Christi and Lake Jackson originated from the Lake Jackson airport. And indeed we do see that when Lake Jackson became the district with platforms dispersed across the largest geographical area, that variation in wind speed across the district became a determinant of inspector group size. As can be seen in Figure 1, after the closure of the Corpus Christi office, the number of inspectors per inspection is more closely correlated with the standard deviation in wind speed across the district. Figure 1 shows quarterly averages of the standard deviation in wind speed at 8 a.m. as well as the daily mean number of inspectors per inspection. As the standard deviation in wind speed across the area increases, so does the number of inspectors sent on an inspection, and this is particularly pronounced after all inspections originated from the same airport. Later we discuss in more detail how daily standard deviation in wind speed can be used as a valid instrument for inspector group size.

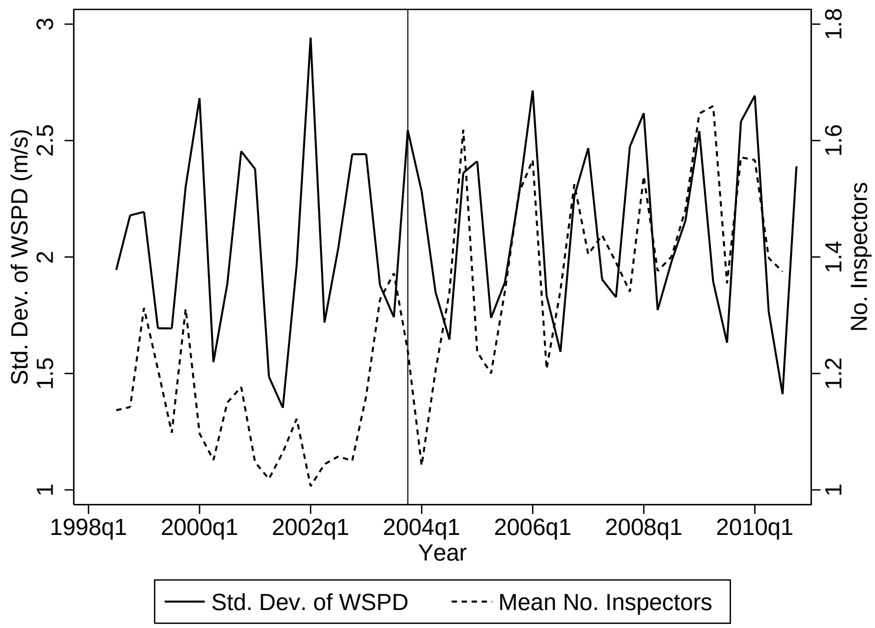



FIGURE 1.— Instrumenting for the Number of Inspectors with Variation in Wind Speed. Quarterly data obtained by averaging the 8 a.m. standard deviation of wind speed across Corpus Christi and Lake Jackson. Vertical line indicates when Corpus Christi was incorporated into the Lake Jackson district.

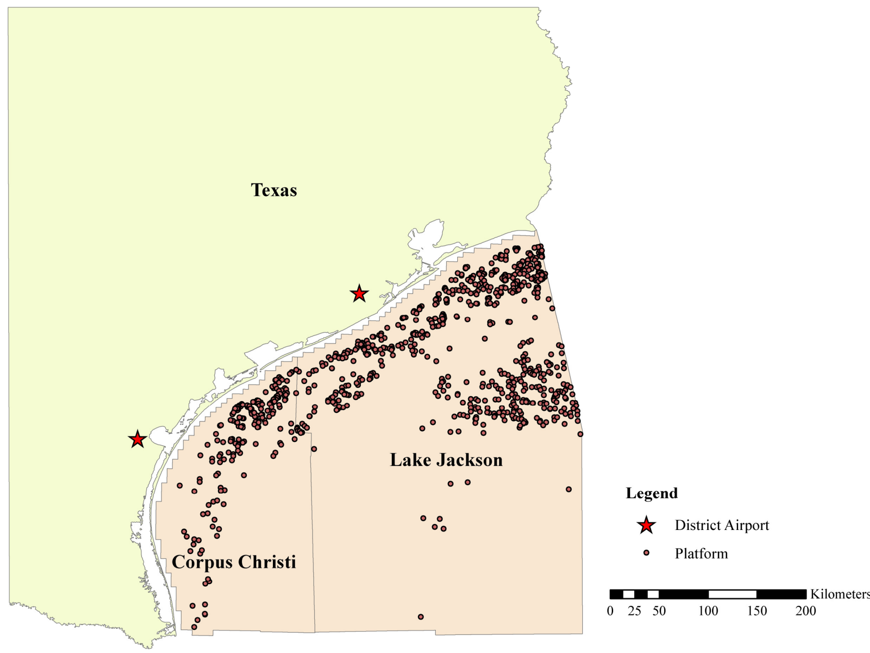



FIGURE 2.— The Boundaries of Lake Jackson and the Former Corpus Christi Subdistrict.

### 3.1. *Estimation Strategy for Group Size Effect*

We are interested in whether increasing the number of inspectors conducting an inspection changes the likelihood that violations of different severity are detected and cited. Inspectors not only might change the aggregate number of INCs they write, but they also might change the distribution of citations given; for example, they may shift from warnings to component shut-ins or from component to facility shut-ins. Thus, we run multiple regressions with different outcome variables including the number of warnings, the number of component shut-ins, and the number of facility shut-ins issued during an inspection. We also examine a weighted combination of the INCs using a formula that BOEMRE uses to calculate an Operator Safety Index: one facility shut-in is equivalent to four warnings or two component shut-ins [Slitor, 2000]. Our variable of interest is the enforcement action (INC) given by inspector (or inspector group), $i$, to platform $p$ at time $t$:

$$\text{(1)} \qquad \text{INC}_{ipt} = \varphi + \vartheta \text{Inspectors}_{ipt} + \mathbf{X}_{ipt}\varrho_1 + mu_t + \upsilon_p + \varepsilon_{ipt}$$

where Inspectors$_{ipt}$ is the number of inspectors that conducted the inspection. We include controls for the platform, inspector, and operator in $\mathbf{X}$. Platform characteristics include age, distance to shore, water depth, production (in the month of the inspection), an indicator for whether the platform is a major complex, whether it is manned 24 hours a day, the number of wells at the platform, and a weighted average of INCs in the past; inspector characteristics include the inspector's propensity to issue INCs, an indicator for whether one of the inspectors is new, the total number of past inspections conducted, and an indicator for whether there is a female inspector present; and operator characteristics include the number of other companies that have a working interest in the lease, the percent working interest of the operator, and the number of other platforms operated by the operator, all measured at the time of the inspection. We also include operator fixed effects, $\upsilon_p$ to account for any non-time varying unobserved characteristics of the operator. We include an indicator for whether the inspection was unannounced, and whether the inspection occurred shortly after a Hurricane. We include a year-month fixed effect, $\mu_t$ to control for district-level trends over time. The term $\varepsilon_{ipt}$ is a mean-zero error term, clustered at the platform level.

A problem arises in estimating equation (1) because the number of inspectors in a group might not be randomly assigned. For example, it is possible that more inspectors are sent to facilities that are prone to violations, and therefore the covariance between the number of inspectors and $\varepsilon_{ipt}$ would be positive. In this example, the ordinary least squares (OLS) estimate of the effect of an additional inspector would be biased upward. Therefore, to deal with the endogeneity of the number of inspectors, we instrument for the number of inspectors using the standard deviation in wind speed across the district on the day of the inspection (SDWSPD). That larger inspection groups are sent during bad weather, the difference in the resulting INCs can be used to measure the local average treatment effect (LATE) of sending more inspectors on the basis of bad weather [Imbens and Angrist, 1994]. Our first-stage equation models the relationship between weather and the number of inspectors:

$$\text{Inspectors}_{ipt} = \alpha + \beta \text{SDWSPD}_t + \mathbf{X}_{ipt}\delta_1 + \mu_t + \varepsilon_{ipt} \tag{2}$$

In order to use the variation in wind speed across the district to measure the LATE, the wind speed variation must also be independent of the error term in the enforcement equation. There would be a problem, for example, if variation in wind speed also meant that there were high winds at the platforms being inspected, which also resulted in a higher number of violations than otherwise would have occurred under normal wind speeds. It is therefore worth noting that mean wind speed across the district on the day of the inspection, the wind speed closest to the platform, and mean wave height across the district, all do not determine the number of enforcement actions (Table IV). This also follows the reasoning that if weather were bad enough to cause structural damage, helicopters would be grounded and we would have no observations of inspections in the first place. Nonetheless, we also include an indicator for post-hurricane inspections, without changing our results. We find that variables capturing the direct effect of weather (mean wind speed in the district, closest wind speed to the platform, etc.) are weak instruments for the number of inspectors, compared to the standard deviation in wind speed across the district, which we find to be a sufficiently strong instrument.

Note that a LATE is not necessarily equal to an average treatment effect. LATE represents a weighted average response to a unit change in treatment, where the weight is proportional to the number of platforms that get an additional inspector because of weather [Imbens and Angrist, 1994, Angrist and Imbens, 1995]. Therefore, the stronger the effect of weather on a particular level of group size increase, the greater the weight placed on the effect of that increase. Measuring a LATE also requires a monotonicity assumption that variation in wind speed would not result in fewer inspectors being sent to a platform. Furthermore, the effect of the extra inspector is revealed only for the platforms that received an additional inspector due to weather. It does not tell us about the effect of an extra inspector on those platforms that would not get an extra inspector even in bad weather. We can only determine the effect on the subpopulation of platforms that had a change in inspector group size because of the weather.

## 4. DATA AND DESCRIPTIVE STATISTICS

We use a dataset of inspections in the Gulf of Mexico obtained from BOEMRE. The dataset contains information on the enforcement action (INC) taken, as well as whether the INC was submitted for civil penalty review or finally rescinded for each inspection. The dataset also contains the names of the inspectors conducting the inspection. With this identifier, we calculate variables such as the number of times an inspector visited the platform prior to the inspection or the fraction of an inspector's past inspections that resulted in an enforcement action. We also keep track of the number of times each combination of inspectors was grouped together in the past. We construct these variables using the full dataset dating back to 1986, and then we examine the effect of these variables on inspections starting in October 2003, following the merger of the Corpus Christi subdistrict into the Lake Jackson district. Using the names of the inspectors in the group we determine whether there was a female inspector present. Table I reports on the summary statistics for the data in our study.

As shown in Table II, there is generally a positive relationship between the number of inspectors and the severity of enforcement action taken. For example, the probability of a facility shut-in more than doubles from 0.02 to 0.055 when moving from one to two inspectors, and increases further to 0.113 with three inspectors and 0.133 with four or more. On the other hand, the least stringent enforcement measure, warnings, actually decreases slightly from 0.459 to 0.407 when a second inspector is added. As a placebo test, we use the standard deviation in wind speed exactly one year after the inspection as the instrumental variable. In this case, the coefficient on the standard deviation is insignificant in the first stage regression, the F-stat for weak instrument is 1.329, and all coefficients in the second stage are insignificant. Using the standard deviation in wind speed the day before *and* the day after the inspection results in a first stage F-statistic of .1 and all affected coefficients are insignificant.

TABLE I

Summary Statistics

| | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| **Weather Variables**: | | | | |
| Std. Dev. WSPD (m/s) | 1.89 | .923 | .269 | 6.29 |
| Mean WSPD (m/s) | 7.27 | 2.44 | 1.5 | 18.8 |
| WSPD at Closest Buoy | 7.32 | 3 | .488 | 20.7 |
| Hurricane (2 months post) | .0891 | .285 | 0 | 1 |
| **Platform Characteristics**: | | | | |
| Platform Age (years) | 14.9 | 10.2 | 0 | 53 |
| Distance to Shore (miles) | 43.8 | 35.3 | 4 | 156 |
| Water Depth (1,000 feet) | .191 | .467 | .026 | 4.82 |
| Production (mmBOE in month prior) | .0358 | .152 | 0 | 2.88 |
| Major Complex (Indicator) | .669 | .471 | 0 | 1 |
| Manned 24 hrs (Indicator) | .248 | .432 | 0 | 1 |
| Number of Wells (t) | 4.1 | 5.48 | 0 | 31 |
| Corpus Christi (Indicator) | .203 | .402 | 0 | 1 |
| Inactive (Indicator) | .321 | .467 | 0 | 1 |
| **Inspection Characteristics**: | | | | |
| INC Issued (Indicator) | .377 | .485 | 0 | 1 |
| Most Severe INC=W (Indicator) | .15 | .357 | 0 | 1 |
| Most Severe INC=C (Indicator) | .201 | .401 | 0 | 1 |
| Most Severe INC=F (Indicator) | .0264 | .16 | 0 | 1 |
| No. Warnings | .455 | 1.04 | 0 | 10 |
| No. Component Shut-ins | .483 | 1.35 | 0 | 16 |
| No. Facility Shut-ins | .0339 | .242 | 0 | 5 |
| No. INCs to Civil Penalty Review | .0329 | .221 | 0 | 3 |
| Rescinded INCs | .0169 | .166 | 0 | 4 |
| Unannounced (Indicator) | .00149 | .0386 | 0 | 1 |
| No. Inspectors | 1.36 | .608 | 1 | 6 |
| Time Since Last Insp. (days) | 342 | 128 | 2 | 1139 |
| **Inspector Characteristics**: | | | | |
| New Inspector (Indicator) | .0309 | .173 | 0 | 1 |
| Past Inspections$_{\mathrm{I}}$ (100s) | 8.48 | 6.22 | .06 | 21.1 |
| Cum. INCs$_{\mathrm{I}}$/Cum. Inspections$_{\mathrm{I}}$ (t-1) | 143 | 50.3 | 17.4 | 339 |
| Female (Indicator) | .155 | .362 | 0 | 1 |
| Cum. Inspections of P by I (t-1) | 1.12 | 1.63 | 0 | 11 |
| First Time (P,I) | .612 | .488 | 0 | 1 |
| **Ownership and Operator:** | | | | |
| No. of Lessees (t) | 2.58 | 1.94 | 1 | 12 |
| Working Interest of O (%) (t) | 57 | 39.5 | 0 | 100 |
| No. of P Operated by O (t) | 127 | 124 | 1 | 597 |
| Observations | 2008 | | | |

*Notes:* Sample includes production inspections on offshore facilities in Lake Jackson October 2003 to August 2010. W=Warning, C=Component Shut-in, F=Facility Shut-in, P=Platform, O=Operator, I=Inspector, (O,I)=Inspections of Operator O by Inspector I. For all inspector variables (I), if the inspection was conducted by a group, the variable is the average over all group members.

TABLE II

Means (and Standard Deviations) by Number of Inspectors

| | One | Two | Three | Four+ |
|---|---|---|---|---|
| No. Warnings | .459 | .407 | .635 | .667 |
| | (1.080) | (.984) | (1.307) | (1.113) |
| No. Component Shut-ins | .404 | .499 | 1.017 | 1.267 |
| | (1.212) | (1.345) | (2.256) | (1.438) |
| No. Facility Shut-ins | .020 | .055 | .113 | .133 |
| | (.204) | (.301) | (.435) | (.352) |
| No. INCs to Civil Penalty Review | .050 | .053 | .096 | .067 |
| | (.379) | (.475) | (.458) | (.258) |
| Rescinded INCs | .020 | .019 | .009 | .000 |
| | (.226) | (.175) | (.093) | (.000) |
| Observations | 1769 | 675 | 115 | 15 |

*Notes:* Sample includes production inspections in Lake Jackson October 2003 to August 2010. Means are reported with standard deviations in parentheses. There is only one observation with six inspectors, and none with five.

### 4.1. *Platform Characteristics*

Two datasets[10]containing platform characteristics from BOEMRE were used to create a panel of every platform in the Gulf of Mexico from the year the platform was first installed through 2010. The dataset contains information on the distance to shore, water depth, lease number, and whether or not there are personnel on board 24 hours a day. There is also an indicator of whether the platform is considered to be a "major complex" (defined as a platform that has at least one structure with at least six completions or two pieces of production equipment).

Many platforms in the Gulf of Mexico are not producing, and those that are producing vary widely in the amount of oil and gas produced. Production data for all wells in the Gulf of Mexico from 1996 to 2010 were also obtained online from BOEMRE.[11] This dataset contains a unique well identifier (the API well number), monthly produced gas volume and oil volume, and days on production. Using BOEMRE's dataset on boreholes,[12] we assigned a platform identifier to the API well numbers so that we could aggregate the monthly well production to monthly platform production. We also created a variable for the number of wells at each platform.

### 4.2. *Lease Owners and Designated Lease Operators*

A single lease can have many owners with different percentages of ownership (working interests). A lease may also be divided into different aliquots, or portions, and each aliquot may have multiple working interests. Data on the lease ownership and designated operator of a lease were obtained online from BOEMRE.[13] These data contain the working interest of all owners of offshore Gulf leases, including all ownership changes from the assignment date

[10] "Platform Masters" and "Platform Structures" found online at https://www.data.boem.gov/homepg/data_center/platform/platform.asp

[11] Production Data: http://www.data.boem.gov/homepg/pubinfo/freeasci/product/freeprod_ogora.asp

[12] Borehole Data: https://www.data.boem.gov/homepg/data_center/well/well.asp

[13] Lease Data: https://www.data.boem.gov/homepg/data_center/leasing/leasing.asp

of the lease to present. We constructed variables for the number of companies that had an interest in the lease in that year, and the mean percentage working interest in the lease.

At any one point in time, however, there is only one designated operator of the lease. The operator, as defined by BOEMRE, is either the leaseholder or the party designated (and approved) to operate a portion of a given lease.[14] A record of platform operators (received from BOEMRE) was used to determine the operator of a platform at the time of the inspection. BOEMRE gives each subsidiary of a company a different company identification number. For example, Shell Offshore Inc. has 10 subsidiaries in the Gulf of Mexico (including, for example, Shell Consolidated Energy Resources Inc., Shell Deepwater Development Inc., Shell Oil Company), each of which has a unique company number. In order to match the subsidiaries to their parent companies, we used an unofficial list of parent-subsidiaries obtained from BOEMRE. For the remainder of unmatched observations, the parent company found in BOEMRE's operator safety summaries was used. If the platform operator was missing five years before the assignment date, the designated operator at the time of the assignment was used. With this information we constructed variables for the number of platforms that the parent company operates, and the working interest of the platform operator.

### 4.3. *Buoy Data*

Weather can determine if inspectors will be able to conduct an inspection. Helicopters to unmanned structures are typically suspended when wind speed is 27–30 m/s (60–67 mph), and all flights are suspended when wind speed is higher than 30 m/s (67 mph) [International Association of Oil & Gas Producers, 2005]. This is consistent with what is observed for wind speed on days of inspections–the maximum wind speed measured at a buoy closest to the platform is 20.7 m/s. Although visibility, cloud ceiling, and the presence of lightning also

[14] A platform operator is typically the responsible party in the event of an oil spill. However, in some instances a platform ties in production from a subsea lease that is miles away and could be leased to a different operator. Under U.S. government regulations, all three parties (the surface platform operator, the subsea lessee, and the pipeline right-of-way holder) are required to show oil spill financial responsibility.

determine whether flying is an option, it is not possible to obtain these data over the Gulf of Mexico.

Wind speed data over the Gulf were obtained from the National Data Buoy Center (NDBC) of the National Oceanic and Atmospheric Administration (NOAA). Buoy stations record hourly standard meteorological and wave data. Wind speed is the most often recorded variable whereas temperature and wave height are often missing. There are eight NDBC deployed buoys stationed off the coast of Texas. Only five of these buoys have data spanning the dates studied. We use the wind speed recorded at 8:00 a.m. of the day of the inspection because helicopters transporting inspectors attempt to take off earlier than 7:15 a.m. [Offshore Energy and Minerals Management, 2009].[15]

### 4.4. *Sample Construction*

In using weather as an instrument we restrict the analysis to production inspections of offshore platforms in Lake Jackson after it subsumed the Corpus Christi subdistrict in 2003.[16] We chose Lake Jackson because since 2003, compared to other districts in the Gulf of Mexico, the platforms in Lake Jackson are spread over the largest area (see Figure 5 in the Appendix for a map of the Gulf). In the other districts, which have more platforms and cover smaller areas, bad weather might result in the grounding of all flights, not just the grounding of flights to a portion of the district. Therefore, in Lake Jackson it is more likely for there to be variation in weather across the district, and thus more likely for weather to affect the number of inspectors sent to a platform than in a geographically smaller district.

There were 13 different inspection types; however, 81% were classified as an annual production inspection. We restrict the sample to only include these inspections, because they

[15] We convert wind speeds to 20 meters above the surface using the formula $\text{WSPD}(20\text{ meters}) = \text{WSPD}(z)(\frac{20}{z})^{1/7}$ where $z$ represents the height above the surface at which observations are collected [U.S. Army Coastal Engineering Research Center, 1984].

[16] The number of different platforms that existed in each district (1986–2010): 131, Corpus Christi; 1,397, Houma; 1,177, Lafayette; 992, Lake Charles; 696, Lake Jackson; 1,182, New Orleans.

are more uniform in how they are conducted and in the type of INC issued.[17] However, when we construct variables on inspectors, such as the number of inspections an inspector conducted in the past, we include all inspection types. Also, when the inspection has more than one inspector, the inspector variables are averaged over all inspectors in the group. For example, the number of prior inspections (Past Inspections$_I$) is the number of prior inspections averaged over all inspectors in the group. These variables are cumulative including all inspections from 1986 to the current inspection.

### 4.5. *Results Using Weather as an Instrument for Group Size Effects*

We consider the outcome of an inspection to be the number and types of INCs issued to platform $p$ when assigned $N$ number of inspectors. Variation in weather across the district is used to instrument for the number of inspectors. The outcomes, warnings, component shut-ins, facility shut-ins, and a weighted combination of these enforcement actions are estimated separately using OLS and instrumental variables (IV) estimation.

One potential problem with estimating this model is that we are analyzing inspections that are mandated to occur at least once a year. If inspections occurred exactly every 12 months, considering that weather is seasonal, we might have a compounded effect from consistently having fewer (or more) inspectors at a platform. However, as shown in Table I, there is variation in the time since the last inspection as well as variation in wind speed within each month. As shown in Table III, baseline characteristics, such as the INCs received in the inspection prior, do not to vary across platforms inspected on highly variable days.

We show in Table IV that the mean wind speed in the district on the day of the inspection, the wind speed closest to the platform and the average wave height, does not have an effect on the enforcement action taken.[18] It still could be possible that high variation in wind speed

[17]When including all inspection types, our instrument becomes too weak (Stock and Staiger [1997] suggest the first stage F-statistic should be greater than ten).

[18]In the specification shown in Table IV, all covariates that are included in the main regression (Table VI) are also included; however, not including these covariates also does not result in statistical significance on

coincides with incidents of non-compliance issued because of damage from hurricanes. We do not find that an indicator for inspections that occurred after a hurricane[19] are statistically significant in determining the number of inspectors or the enforcement action taken.

mean wind speed on the day of the inspection, the wind speed measured at the buoy closest to the platform, nor the average wave height. Due to space constraints the weighted average of the INCs is not included, but all coefficients are also statistically insignificant in the weighted average INC regression.

[19]We also tried various intervals ranging from one week to 16 weeks after a hurricane. The coefficients displayed under "Post Hurricane" in Tables V and VI refer to an indicator for any inspection that occurred within eight weeks after Hurricanes Ivan, Katrina, Rita, Gustav, and Ike.

TABLE III

Baseline Characteristics by Standard Deviation in Wind Speed

| | (1) C.C. | (2) INCs(t-1) | (3) Dist. | (4) Age | (5) Depth | (6) Prod. | (7) Major | (8) Manned | (9) Wells |
|---|---|---|---|---|---|---|---|---|---|
| Std. Dev. WSPD | .001 | .056 | .553 | -.056 | .008 | .003 | .001 | -.019 | -.214 |
| | (.009) | (.072) | (.731) | (.276) | (.015) | (.007) | (.013) | (.014) | (.140) |
| n | 2,008 | 2,008 | 2,008 | 2,008 | 2,008 | 2,008 | 2,008 | 2,008 | 2,008 |
| $R^2$ | .42603 | .11290 | .38491 | .40955 | .37693 | .29976 | .20590 | .27287 | .34943 |

*Notes:* Columns represent OLS coefficients with robust standard errors clustered by operator (for 91 operators). Dependent variables are platform characteristics: an indicator for whether the platform was in the Corpus Christi sub-district (CC), a weighted average of the INCs from the most recent prior inspection (INCs=W+2C+4F), distance to shore, age, depth, past month's production, whether the complex is a major complex, whether it is manned 24 hours a day, and the number of wells present. Year-month and operator fixed effects included in all regressions (coefficients not reported). Sample includes production inspections in Lake Jackson October 2003 to August 2010. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

TABLE IV

Direct Effect of Weather on Outcome of Inspection

| | Warnings | | | Component | | | Facility | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Mean WSPD | .004 | | | .011 | | | -.001 | | |
| | (.013) | | | (.013) | | | (.003) | | |
| WSPD at Closest Buoy | | -.002 | | | .006 | | | .000 | |
| | | (.009) | | | (.012) | | | (.003) | |
| Mean Wave Height | | | -.047 | | | -.005 | | | -.006 |
| | | | (.063) | | | (.066) | | | (.018) |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| n | 2,008 | 2,000 | 1,787 | 2,008 | 2,000 | 1,787 | 2,008 | 2,000 | 1,787 |
| Mean of Dep. Var. | .45518 | .45600 | .46391 | .48257 | .48450 | .48461 | .03386 | .03400 | .03525 |

*Notes:* Sample includes production inspections in Lake Jackson between October 2003 and September 2010. Dependent variables are the number of warnings (W), component shut-ins (C), and facility shut-ins (F). Controls also include all covariates from the baseline regression (Table VI). Robust standard errors are clustered by operator (for 91 operators). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table V reports the first stage relationship between inspectors and the standard deviation in wind speed in the instrumental variables estimation. For our purposes, the important finding is that the number of inspectors is positively related to wind speed variability, consistent with Figure 1. We find a strong first stage relationship; the first stage F-statistic ranges from 8.9 to 18.3, depending on the specification. The first stage contains the included exogenous variables of the second stage. Interestingly, the number of inspectors is unrelated to the production level, complexity, or prior compliance history of the production platform. There does not appear to be evidence of targeting more inspectors to the worst platforms. We find that including an indicator for whether one of the inspectors has conducted fewer than 25 inspections prior to the inspection is positive and significant. These inspectors could be considered trainees, and we find they are statistically significantly more likely to go in an inspection group than on their own. We also note that the past enforcement tendencies of the inspectors is not statistically significant in determining the inspection group size (that is, the cumulative INCs issued divided by the number of inspections conducted). It is possible that some targeting of inspectors is taking place in determining the number of inspectors to send, with the most stringent inspectors sent alone or in relatively smaller groups. This targeting would bias our estimate of the effect of an additional inspector downward.

Table VI reports on our main regression results relating the number of inspectors to the resulting enforcement actions. This table shows both OLS and IV results. We see that the most stringent enforcement action, facility shut-ins, are statistically significantly more likely to occur with more inspectors. Focusing on the last two columns, where enforcement actions are weighted, we see that adding an inspector has a positive impact on the likelihood that an enforcement action will be taken at the 10% level. Also included as a control variable is the weighted average INC at the platform in the prior period. This variable is positive and significant at the 10% level, suggesting that noncompliance is persistent. Of course, it is possible that in the absence of any prior period INCs, platforms would have been even

TABLE V

First Stage: Number of Inspectors

| | (1) |
|---|---|
| Std. Dev. WSPD | .061*** |
| | (.022) |
| **Included Exogenous Variables:** | |
| Platform Age (years) | .001 |
| | (.002) |
| Distance to Shore (miles) | -.002*** |
| | (.001) |
| Water Depth (1,000 feet) | .117** |
| | (.049) |
| Inactive (Indicator) | -.032 |
| | (.027) |
| Production (mmBOE in month prior) | .291** |
| | (.119) |
| Major Complex (Indicator) | .038 |
| | (.030) |
| Manned 24 hrs (Indicator) | .057 |
| | (.039) |
| Number of Wells (t) | .005 |
| | (.004) |
| Corpus Christi (Indicator) | -.085** |
| | (.039) |
| Weighted INCs (t-1) | -.002 |
| | (.006) |
| Cum. $INCs_I$/Cum. $Inspections_I$ (t-1) | .000 |
| | (.000) |
| New Inspector (Indicator) | .755*** |
| | (.157) |
| Cum. Inspections by I (t-1) | -.015*** |
| | (.003) |
| Female (Indicator) | .155** |
| | (.062) |
| Unannounced (Indicator) | .262 |
| | (.211) |
| No. of Lessees (t) | .003 |
| | (.010) |
| Working Interest of O (%) (t) | .000 |
| | (.000) |
| No. of P Operated by O (t) | -.000 |
| | (.001) |
| Post Hurricane (Indicator) | -.012 |
| | (.204) |
| Year-Month Effects | Yes |
| Operator Effects | Yes |
| n | 2,008 |
| Mean of Dep. Var. | 1.36404 |
| $R^2$ | .27260 |

*Notes:* Sample includes production inspections in Lake Jackson between October 2003 and September 2010. Columns represent OLS coefficients. Dependent variable is the number of inspectors. Robust standard errors are clustered by operator (for 91 operators). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

worse, so we are not making any claims about the deterrent effect of INCs.

We also control for production levels, platform complexity, and other factors. Note that we also include a control variable indicating when one of the inspection team is a new inspector (i.e., he or she has conducted fewer than 25 inspections); since new inspectors might be more in a training/shadowing mode, adding a "first time" inspector might have different implications than adding a random inspector-these inspections are not statistically different other than being less likely to issue a facility shut-in. Thus, even after any targeting, we find that increasing the number of inspectors yields an increase in stringent enforcement actions.

The coefficient on the number of inspectors is always larger when using the IV specification compared to OLS. Besides endogeneity, there could be two other reasons driving this result– measurement error in group size and non-linearity in the effect of group size. For this paper, the data contain detailed records of the number of inspectors on the platform; it could be the case that some inspectors were only present during part of the inspection, however, measurement error in the number of inspectors is not as likely as non-linearity in the effects. The IV estimates use variation in the inspection group size induced by wind speed, whereas OLS estimates use all the variation. If weather affects a particular level shift in the group size and this level shift has a larger effect on enforcement, then the IV and the OLS estimates will differ. We find that the instrument has the largest effect in increasing the number of inspectors from one to two (Table VII, column 1), less of an effect in moving the number of inspectors from two to three (column 2), and no statistically significant effect in moving from three to four or more (column 3). To examine whether there are non-linearities in the enforcement actions by inspection group size, we estimate the OLS specifications in Table VI using dummies for each level of group size instead of the count of inspectors. This gives us a separate coefficient on each group size level: moving from one to two or more, three or more, and four or more inspectors (Table IX). In most cases, F tests reject the null

## TABLE VI
### Impact of the Number of Inspectors on Enforcement Actions

| | Warnings | | Component | | Facility | | Weighted | |
|---|---|---|---|---|---|---|---|---|
| | (1) OLS | (2) IV | (3) OLS | (4) IV | (5) OLS | (6) IV | (7) OLS | (8) IV |
| No. Inspectors | .089 | .417 | .254*** | .570 | .035** | .238** | .735*** | 2.508 |
| | (.054) | (.689) | (.049) | (.625) | (.015) | (.112) | (.142) | (1.688) |
| Platform Age (years) | .011** | .011* | .007 | .007 | .000 | -.000 | .025 | .023 |
| | (.005) | (.005) | (.006) | (.005) | (.001) | (.001) | (.018) | (.018) |
| Distance to Shore (miles) | .002** | .003* | .002* | .003 | .000 | .001** | .007** | .010** |
| | (.001) | (.001) | (.001) | (.002) | (.000) | (.000) | (.003) | (.004) |
| Water Depth (1,000 feet) | .145* | .106 | -.032 | -.070 | -.020 | -.044** | -.001 | -.210 |
| | (.080) | (.087) | (.268) | (.274) | (.012) | (.019) | (.605) | (.639) |
| Inactive (Indicator) | -.169*** | -.159*** | -.267*** | -.258*** | -.008 | -.002 | -.736*** | -.684*** |
| | (.058) | (.059) | (.059) | (.056) | (.014) | (.015) | (.191) | (.187) |
| Production (mmBOE in month prior) | -.564*** | -.662* | -.379 | -.473 | -.011 | -.071 | -1.365 | -1.891 |
| | (.195) | (.340) | (.505) | (.530) | (.039) | (.058) | (1.137) | (1.334) |
| Major Complex (Indicator) | .100* | .087* | .151** | .139** | .019 | .011 | .480*** | .410** |
| | (.060) | (.050) | (.061) | (.065) | (.012) | (.012) | (.170) | (.171) |
| Manned 24 hrs (Indicator) | .054 | .037 | .242 | .226 | -.014 | -.024 | .483 | .392 |
| | (.085) | (.084) | (.181) | (.178) | (.017) | (.018) | (.466) | (.439) |
| Number of Wells (t) | -.013** | -.015*** | .009 | .007 | .004*** | .003** | .019 | .011 |
| | (.005) | (.006) | (.008) | (.009) | (.001) | (.001) | (.018) | (.019) |
| Corpus Christi (Indicator) | .033 | .062 | .052 | .079 | .025 | .042 | .235 | .388 |
| | (.086) | (.115) | (.136) | (.152) | (.023) | (.027) | (.321) | (.361) |
| Weighted INCs (t-1) | -.007 | -.007 | .010 | .011 | .001 | .002 | .019 | .021 |
| | (.005) | (.004) | (.009) | (.009) | (.001) | (.001) | (.024) | (.022) |
| Cum. $\text{INCs}_{\text{I}}$/Cum. $\text{Inspections}_{\text{I}}$ (t-1) | .005*** | .005*** | .003** | .002** | .000 | .000 | .011*** | .011*** |
| | (.001) | (.001) | (.001) | (.001) | (.000) | (.000) | (.003) | (.002) |
| New Inspector (Indicator) | .053 | -.194 | -.128 | -.366 | -.024 | -.176** | -.300 | -1.632 |
| | (.143) | (.558) | (.209) | (.527) | (.021) | (.086) | (.460) | (1.500) |
| Cum. Inspections by I (t-1) | .007 | .012 | .004 | .008 | -.003** | .000 | .003 | .030 |
| | (.005) | (.013) | (.008) | (.012) | (.001) | (.002) | (.021) | (.032) |
| Female (Indicator) | .158** | .110 | -.194*** | -.240* | -.029 | -.058* | -.345* | -.604** |
| | (.068) | (.098) | (.072) | (.126) | (.019) | (.030) | (.206) | (.306) |
| Unannounced (Indicator) | .662 | .576 | -.349* | -.432 | -.000 | -.053 | -.037 | -.498 |
| | (.575) | (.565) | (.205) | (.276) | (.029) | (.075) | (.907) | (1.185) |
| No. of Lessees (t) | -.011 | -.012 | .012 | .011 | -.001 | -.002 | .008 | .003 |
| | (.020) | (.018) | (.023) | (.021) | (.003) | (.003) | (.065) | (.054) |
| Working Interest of O (%) (t) | .001 | .001 | .001 | .001 | .000 | .000 | .004 | .004 |
| | (.001) | (.001) | (.001) | (.001) | (.000) | (.000) | (.003) | (.003) |
| No. of P Operated by O (t) | .001 | .002 | -.002 | -.002 | -.000 | -.000 | -.004 | -.003 |
| | (.001) | (.001) | (.002) | (.002) | (.000) | (.000) | (.004) | (.004) |
| Post Hurricane (Indicator) | -.313 | -.315 | -.070 | -.072 | .010 | .009 | -.412 | -.422 |
| | (.234) | (.248) | (.325) | (.336) | (.026) | (.051) | (.802) | (.956) |
| Year-Month Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Operator Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| n | 2,008 | 2,008 | 2,008 | 2,008 | 2,008 | 2,008 | 2,008 | 2,008 |
| Mean of Dep. Var. | .45518 | .45518 | .48257 | .48257 | .03386 | .03386 | 1.55578 | 1.55578 |
| First Stage F-stat. | | 14.38692 | | 14.38692 | | 14.38692 | | 14.38692 |

*Notes:* Sample includes production inspections in Lake Jackson between October 2003 and September 2010. Dependent variables are the number of warnings (W), component shut-ins (C), facility shut-ins (F), or *Weighted*, a weighted combination of all INCs (Weighted=W+2C+4F). In the case of the IV estimates, *No. Inspectors* is instrumented for using weather. Robust standard errors are clustered by operator (for 91 operators). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

that the coefficients are equal.[20] Therefore, it appears that the true relationship between the enforcement actions and the number of inspectors is non-linear, but because we do not have enough instruments, we have estimated a linear model and restricted the effect to be constant. Weights for IV estimators in the presence of non-linearity have been derived by Angrist and Imbens [1995], Heckman et al. [2006] and Lochner and Moretti [2011]. Following Lochner and Moretti [2011] we re-weight the OLS estimates of in Table IX using estimated IV weights, and use a general Wald test, robust to a non-linear relationship between the endogenous regressors and the dependent variable, to test for exogeneity.[21] The re-weighted OLS coefficients are larger than the OLS estimates (Table IX), however the re-weighted OLS coefficients are still smaller than the IV estimates. Using the general Wald test, we cannot reject the null hypothesis of exogeniety. Therefore, we have some confidence in the OLS estimates, however, the IV estimate, which is the weighted average of the marginal effects is still useful for guiding inspection policy.

Theoretically we might also expect that moving from one to two inspectors would be different from moving from two to three, because there are multiple orders of free-riding [Yamagishi, 1986, Heckathorn, 1989, Ostrom, 1990, Henrich and Boyd, 2001, Boyd et al., 2003]. Inspectors can contribute a "first-order" public good, which in the case of this paper would refer to inspectors performing their duty to detect and issue INCs; not performing their duty would be termed first-order free-riding. Since punishing any first-order free-riding would take effort, then by enforcing first-order participation, inspectors can contribute a "second-order" public good, which in this case would refer to enforcing fellow inspectors to detect and issue INCs. Not punishing the first-order free-riding is termed second-order free-riding. In the case of second-order free-riding, moving from a group of two to three inspectors would likely have a different effect than moving from one to two.

[20] The p-values that the first two coefficients are equal, for the four specifications are 0.0619, 0.0162, 0.0668, and 0.0024; the p-values that the three are equal are 0.1745, 0.0432, 0.1654, and 0.0095.

[21] If the true relationship between the number of inspectors and enforcement is non-linear, then the traditional Hausman test is uninformative.

TABLE VII

Instrument's Effect on Level Shifts in Group Size

| | (1) More than 1 | (2) More than 2 | (3) More than 3 |
|---|---|---|---|
| Std. Dev. WSPD | .040** | .020** | .001 |
| | (.018) | (.008) | (.001) |
| Controls | Yes | Yes | Yes |
| n | 2,008 | 2,008 | 2,008 |
| Mean of Dep. Var. | .30478 | .05129 | .00697 |

*Notes:* Each column represents a separate OLS regression of variation in wind speed on indicators for whether there were more than 1, 2, or 3 inpectors in the group. All regressions include the same controls as in previous regressions. Sample includes production inspections in Lake Jackson between October 2003 and September 2010. Robust standard errors are clustered by platform (for 562 platforms). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

TABLE VIII

Estimates at Each Level Increase in Group Size

| | (1) Warnings | (2) Component | (3) Facility | (4) Weighted |
|---|---|---|---|---|
| Two Inspectors | .045 | .158** | .020 | .440** |
| | (.060) | (.071) | (.016) | (.199) |
| Three Inspectors | .350** | .717*** | .112** | 2.231*** |
| | (.168) | (.218) | (.050) | (.562) |
| Four or More Inspectors | .078 | .569 | .036 | 1.360 |
| | (.317) | (.383) | (.081) | (1.220) |
| Controls | Yes | Yes | Yes | Yes |
| n | 2,008 | 2,008 | 2,008 | 2,008 |
| Mean of Dep. Var. | .45518 | .48257 | .03386 | 1.55578 |

*Notes:* Each column represents a separate OLS regression of indicators for the size of the group on the enforcement actions (W, C, F, and W+2C+4F). All regressions include the same controls as in previous regressions. Sample includes production inspections in Lake Jackson between October 2003 and September 2010. Robust standard errors are clustered by platform (for 562 platforms). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

TABLE IX

Re-weighted OLS Coefficients

| | Warnings | | Component | | Facility | | Weighted | |
|---|---|---|---|---|---|---|---|---|
| | (1) OLS | (2) ROLS | (3) OLS | (4) ROLS | (5) OLS | (6) ROLS | (7) OLS | (8) ROLS |
| Inspectors | .101* | .234*** | .257*** | .250*** | .036** | .041** | .758*** | .767*** |
| | (.054) | (.052) | (.060) | (.072) | (.016) | (.017) | (.177) | (.208) |
| General Wald (p-value) | | .312 | | .388 | | .151 | | .215 |

*Notes:* OLS estimates are the same as found in Table VI. Re-weighted OLS estimates from derived by using IV weights to calculate an average of the coefficients in Table . The General Wald test [Lochner and Moretti, 2011] compares the re-weighted OLS in this table to the linear IV estimator (found Table VI).

## 5. TESTING FOR REGULATORY CAPTURE USING THE CLOSURE OF AN INSPECTIONS OFFICE

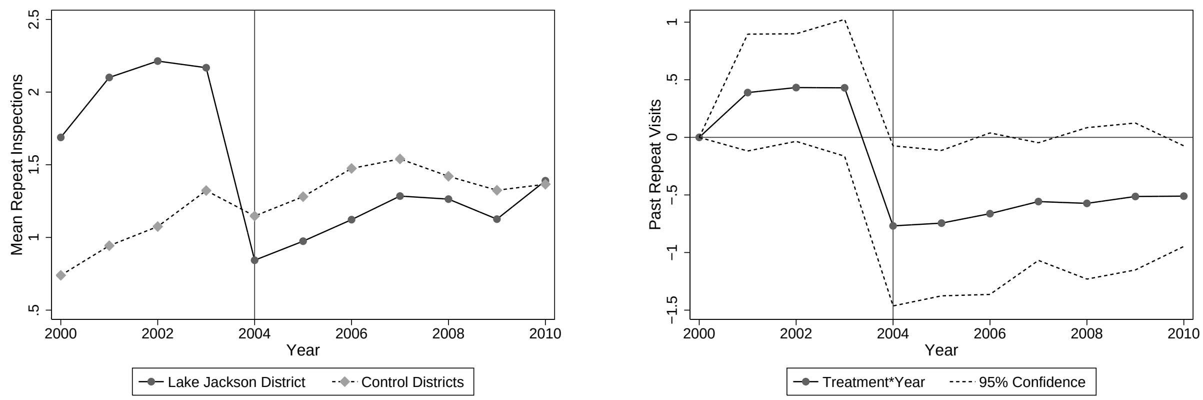
If the goal of the enforcer is to detect and sanction all violations, then we show that this goal is not being met—more violations can be found and cited if more inspectors are available to inspect. Our finding could be driven by the current inspection system being under staffed and inspections not being fully effective. If the marginal cost of finding and citing violations is increasing, then we would expect that the first inspector would find the most, and the easiest, while the additional inspectors would find marginally less, or harder to find violations. If an operator protests the issuance of an INC, an inspector would have to exert more effort to issue the INC. It is the duty of the inspector not to be swayed by any protestations, so it is possible that when there are other members of an inspection group present, they might be more or less likely (depending on the norm of the group) to write up the INC. It is possible that if the group members might act as a united front against any protests by the operator. On the other hand, if the inspectors are inclined to side with the operator, the more lenient they may be. For example, Chen and Li [2009] find that in a laboratory experiment, ingroup members (i.e., members of a group that have identified with one another, as opposed to outgroup members who have not) are less likely to punish an ingroup match for misbehavior. The more familiar an inspector is with the operator, the more likely an inspector is to identify with the operator, and the more likely it is that the regulator is captured. In response to allegations about such potential conflicts of interest, BOEMRE issued a new ethics policy in 2011 requiring individuals in the Gulf district offices to recuse themselves in dealings with companies with a personal family or past employment relationship. According to a news report, approximately 30% of district employees recused themselves from one or more companies operating in the Gulf region in 2011.[22] Therefore, by adding an additional inspector, INC severity increases because not all inspectors are captured, and it is harder for the operator to capture the inspectors because there are more

[22] "Ethics Policy Quantifies Oil Industry–Gov't Ties," Associated Press, July 26, 2011.

to capture. Our instrument is not able to find a statistically significant increase in warnings, but only on the more stringent violations, which suggests that regulatory capture or group norms might have an impact on inspector behavior.

We do not know the background or employment history of the inspectors, and thus cannot directly test for industry identification or an inspector's prospect for future industry employment. However, we do have data on the prior inspections each inspector completed from 1986 to the date of the inspection. The more times that an inspector has visited the same platform, the more familiar they might be with the platform's flaws, and prior violation history, that detecting violations might be easier. On the other hand, the more times that the inspector has visited the same platform, the more they might identify with the operator, and the more pressure they might have to endure to overlook a violation. Measuring the effect of repeated visits is also difficult considering two forms of endogeniety. First, poor performers or older platforms would have had more inspections in the past and might also have had more enforcement actions. This bias runs in the opposite direction from, and would not be the cause of, a finding that more inspections by the same inspector result in fewer enforcement actions. Second, if inspectors have any leeway in choosing where to inspect, the repeat assignment of inspectors to the same platform may be driven by unosbservables correlated with the outcome we are interested in.

Therefore, we also exploit exogenous variation in the number of times an inspector has visited the same platform by examining the closure of the Corpus Christi sub-district in more detail. With the closure of the airport, the average number of times that an inspector had inspected a platform in the past decreased (Figure 4(a)). We estimate a difference-in-difference model, where platforms in Lake Jackson (which includes the Corpus Christi sub-district) are our treatment group, and platforms in all other regions are our control group. The treatment is the decreased number of prior visits, and this treatment occurs in the period that is post-closure of the Corpus Christi sub-district, $\text{Post}_t$, and only on the




(a) Mean number of visits by inspector prior to inspection.

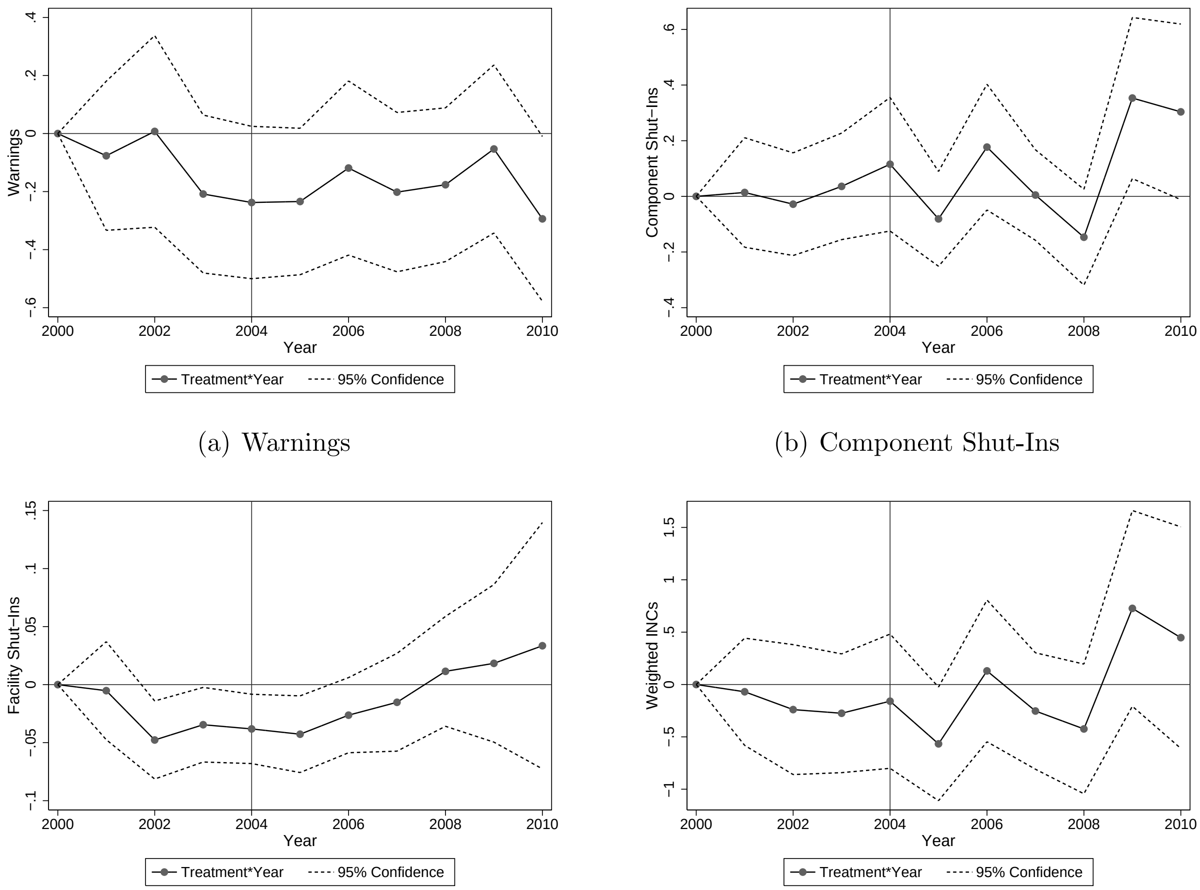
(b) Difference-in-Difference Coefficients for (Treatment * Year Indicators)

FIGURE 3.— The Corpus Christi inspections office was closed in 2003, after which the number of repeat inspections significantly decreased.

platforms in Lake Jackson (or the Corpus Christi sub-district), $\text{LJCC}_p$. In a regression of number of times inspector, $i$, has visited platform, $p$, the coefficient on the interaction of an indicator for Lake Jackson and the post-period, will give us an estimate of the effect of the closure of one of Lake Jackson's airports on repeat visits:

$$y_{ipt} = \delta_0 + \delta_1 \text{LJCC}_p \times \text{Post }_t + \delta_2 \text{ LJCC}_p + \mathbf{X}_{ipt}\delta_4 + \mu_t + \varepsilon_{ipt} \tag{3}$$

With year-month fixed effects, $\mu_t$, we do not include the Post indicator by itself. Table X shows statistically significant reduction in the number of repeat visits in Lake Jackson-Corpus Christi in the post-closure period. To test whether the trends in the pre-period are similar we replace the indicator for the post period in equation 3 with year indicators, and plot the interaction with Lake Jackson-Corpus Christi in Figure 4(b). The coefficients in the pre-period are not significantly different from zero. In columns (2)-(5) of Table X, examine the effect of the closure on enforcement actions, by substituting $y_{ipt}$ in equation 3. We find that component shut-ins are more likely, coinciding with the reduction in repeat visits. Figure 4 graphically displays the interaction with LJCC and year dummies.




(a) Warnings

(b) Component Shut-Ins

(c) Facility Shut-Ins

(d) Weighted INCs

FIGURE 4.— Difference-in-Difference Coefficients for (Treatment * Year Indicators)

TABLE X

IMPACT OF REPEAT VISITS

| | (1) Repeat | (2) Warnings | (3) Component | (4) Facility | (5) Weighted |
|---|---|---|---|---|---|
| LJCC × Post Closure | -1.058*** | -.050 | .198*** | .015 | .404** |
| | (.248) | (.059) | (.053) | (.012) | (.176) |
| LJCC | 1.507*** | .086 | -.123*** | -.005 | -.182 |
| | (.215) | (.057) | (.038) | (.008) | (.137) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| n | 32,442 | 32,442 | 32,442 | 32,442 | 32,442 |
| Mean of Dep. Var. | 1.256 | .359 | .334 | .023 | 1.118 |

*Notes:* Sample includes all platforms in the Gulf of Mexico. The indicator for Lake Jackson district includes platforms that were in the Corpus Christi sub-district. The dependent variables are Repeat=the number of prior visits the inspector made to the same platform; the number of Warnings (W) issued; Component shut-ins (C); Facility shut-ins (F); or *Weighted*, a weighted combination of all INCs (Weighted=W+2C+4F); /*Inspectors=the number of inspectors.*/ Post-Closure= 1 if the inspection occurred after October 2003. Controls include all control variables, with the exception of the number of inspectors. Robust standard errors are clustered by operators (for 304 operators). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

## 6. EVIDENCE OF INCREASED INSPECTION INTENSITY ON DETERRENCE

Most of the environmental economics literature on inspections and enforcement has generally focused on deterrence, i.e., whether increased enforcement activity is correlated with higher compliance and/or improved environmental performance, see Gray and Shimshack [2011] for a thorough review. This stream of literature also only examines deterrence at the extensive margin by measuring the effect of the frequency of inspections; however, little has been said on the effect of increasing inspection intensity.[23] Here we focus on the intensive margin and estimate the effect of increasing the inspection group size on the subsequent number of reported incidents, using incident data obtained from BOERME.

All serious accidents, fatalities, injuries, explosions, and fires are required to be reported to BOEMRE.[24]We regress the number of incidents reported to have occurred on a platform on the number of inspectors who conducted the most recent inspection. Specifically, the outcome variable is the count of the number of incidents that were reported on platform $p$ within a set time period after the inspection ($t + m$ where $m$ is three, six, or nine months).

$$\text{Incident}_{ip(t+m)} = \varphi_0 + \varphi_1 \text{Inspectors}_{ipt} + \mathbf{X}_{ipt}\varphi_2 + \mu_t + \varepsilon_{ipt} \tag{4}$$

$$\text{Incident}_{ip(t+m)} = \vartheta_0 + \vartheta_1 \text{LJCC}_p \times \text{Post}\ _t + \vartheta_2 \text{LJCC}_p + \mathbf{X}_{ipt}\vartheta_4 + \mu_t + \varepsilon_{ipt} \tag{5}$$

The framework is the same as that in the previous estimations: the unit of observation is the inspection, and we instrument for the number of inspectors in the inspection group, because the number of inspectors sent in an inspection group could be correlated with the number of incidents reported. We use the standard deviation in wind speed as an instrument for the number of inspectors (equation 2).

[23]The exception is the analysis of Coast Guard enforcement activities to prevent oil spills from tankers, e.g., Epple and Visscher [1984], Cohen [1987], Grau and Groves [1997], and Gawande and Wheeler [1999]. However, these studies do not examine individual inspections and instead look at aggregate measures such as the number of hours devoted to inspection resources in a district in a quarter.

[24]However, if an inspector discovers that an accident occurred and was not filed within 15 days, the INC they are required to issue is a warning (W). There are potentially severe under reporting of incidents.

TABLE XI

IMPACT OF THE NUMBER OF INSPECTORS ON INCIDENTS REPORTED IN TIME PERIOD AFTER INSPECTION

| | Incident 3 Mo. After | | Incident 6 Mo. After | | Incident 9 Mo. After | |
|---|---|---|---|---|---|---|
| | (1) OLS | (2) IV | (3) OLS | (4) IV | (5) OLS | (6) IV |
| No. Inspectors | -.005 | .008 | .003 | -.071 | .008 | -.039 |
| | (.006) | (.059) | (.009) | (.079) | (.012) | (.100) |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Year-Quarter Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| n | 1,886 | 1,886 | 1,713 | 1,713 | 1,509 | 1,509 |
| Mean of Dep. Var. | .020 | .020 | .036 | .036 | .048 | .048 |
| First Stage F-stat. | | 15.517 | | 18.262 | | 12.980 |

*Notes:* Dependent variables are an indicator for whether one or more incidents were reported, 3 months, 6 months, and 9 months after the inspection. Only inspections without another inspection occurring in these time periods are included. Sample includes production inspections in Lake Jackson from October 2003 to 3 months, 6 months, or 9 months before September 2010. Controls also include all covariates from the baseline regression (Table VI). Robust standard errors are clustered by platform (for 562 platforms). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

The regulations for incident reporting were made more stringent on July 17, 2006 , when it became required to report not only serious incidents, but also incidents that had the potential to be serious (e.g., any incident involving structural damage to a platform, injury that led to an evacuation or days away from work, or property damage exceeding $25,000).[25] Therefore, the regressions for the number of reported incidents include an indicator for periods after this new reporting requirement.

The specification is the same as the baseline specification, except for the inclusion of a new reporting indicator (a post 2006 indicator). We do not find an effect of the inspector group size on the probability of a reported incident occurring (Table XI). Table XII summarizes the variables describing the incidents that occurred within nine months of any inspection. Examining the probability of different incident types being reported also does not show statistical significance in the effect of inspector group size. This could be driven by very few observations, which also does not let us use a detection control mechanism [Feinstein, 1989], to disentangle detection and occurrence. A future draft of this paper will examine the incidents before and after the airport closure.

[25] 30 CFR Part 250, Final Rule (FR 19640), Minerals Management Service, U.S. Department of the Interior.

TABLE XII

Summary Statistics for Incidents Reported

| | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| Accident | .974 | .161 | 0 | 1 |
| Human Error | .118 | .325 | 0 | 1 |
| Equipment Fail | .105 | .309 | 0 | 1 |
| Explosion | .0132 | .115 | 0 | 1 |
| Fire | .316 | .468 | 0 | 1 |
| Spill | .0132 | .115 | 0 | 1 |
| Crane | .118 | .325 | 0 | 1 |
| Structural Damage | .0263 | .161 | 0 | 1 |
| Slip/Trip/Fall | .0395 | .196 | 0 | 1 |
| No. Injuries | .0658 | .377 | 0 | 3 |
| No. Fatalities | .0132 | .115 | 0 | 1 |
| Post-2006 | .789 | .41 | 0 | 1 |
| Observations | 76 | | | |

*Notes:* Summary statistics for incidents reported to have occurred within 270 days of a production inspection in Lake Jackson from October 2003 to March 2010.

## 7. CONCLUDING REMARKS

We find that more inspectors are likely to find more violations; however, due to endogeneity, it is possible that this is the effect of targeting. To test this, we construct an instrumental variable based on exogenous weather-related changes in the number of inspectors sent to inspect a platform. Using this instrument results in a similar finding—more inspectors result in more regulatory violations. While we do not have data on the costs and benefits of inspectors and compliance, our results suggest that at the very least, the current level of staffing at BOEMRE is inadequate to detect all violations. They also suggest that even without an increased enforcement budget, some reallocation of inspector resources might yield increased detection and punishment of violations. The increase in inspectors does not, however, reduce the frequency of oil spills and other incidents reported by companies.

To explain our finding that increased inspectors lead to more stringent enforcement actions, we test for evidence of regulatory capture. We use the count of repeat inspections of the same platform as a measure of familiarity. The more familiarity there is between the inspector and the regulated entity, the more likely it is for regulatory capture. We examine the decrease in repeat inspections on some platforms, due to a closure of an inspections office, and find that repeat visits result in fewer enforcement actions. Future research that identifies the characteristics of individual inspectors might shed further light on this question.

Our study highlights the importance of rigorous empirical analysis of inspections and inspectors as a tool in regulatory compliance. While we focus on offshore oil platforms, the concern that inspectors are not being optimally employed is ubiquitous across regulatory agencies. For example, a recent internal audit of the Mine Safety and Health Administration (MSHA) concluded that "mine inspectors were sometimes lax and inconsistent with their reviews, and some mine inspections weren't conducted according to agency standards and legal requirements."[26] Similarly, a former investigator for the Inspector General's Office of the Nuclear Regulatory Commission recently criticized agency officials: "The N.R.C. is like a prep school for many of these guys, because they know they've got a good shot at landing much higher-paying work with the people they're supposed to be keeping in line. They're not going to do anything to jeopardize that."[27]

While we find more violations would be detected if more inspectors were sent on an inspection, this does not necessarily mean that serious incidents (such as oil spills or injuries) would decrease. And indeed, we do not find evidence that increasing the inspection group size results in fewer serious incidents being reported. Because we find that larger inspector groups issue more severe violations and that these do not translate into fewer incidents being reported, this suggests that the sanctions issued to oil and gas platforms are not stringent enough to reduce the risk of more accidents.

[26] "Internal Audits Reveal Federal Enforcement Lapses," *Energy and Environment Daily*, April 18, 2011.

[27] Tom Zeller, Jr., "Nuclear Agency Is Criticized as Too Close to Its Industry," *New York Times*, Energy and Environment, May 7, 2011.

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## APPENDIX A

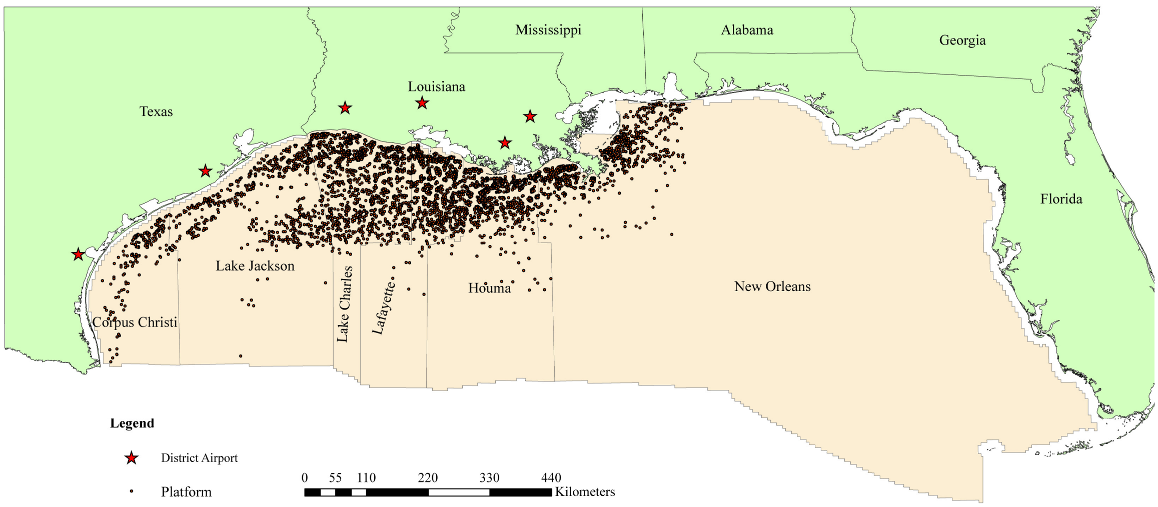


FIGURE 5.— Districts, Platforms, and District Airports in the Gulf of Mexico.

The inspection program is directed by the New Orleans regional office, with inspection offices located in five different districts of the Gulf: Houma, Lafayette, Lake Charles, Lake Jackson, and New Orleans. The New Orleans district covers the largest area in the Gulf of Mexico; however, drilling restrictions off of the coast of Florida have resulted in the Lake Jackson district (including Corpus Christi) to have platforms spread across the largest geographical area.

### A.1. *Outcome of the INCs*

Once an INC is issued by an inspector, the operator of the platform can petition to the BOEMRE district manager to rescind the INC. According to a report by the Office of the Inspector General of the Department of the Interior, "a number of inspectors felt they received insufficient support from management and that, in some cases, management sided with industry when INCs were questioned" and that "INCs are unnecessarily rescinded due to favoritism to some operators" [Office of Inspector General, Department of the Interior, 2010]. The operators have 60 days to appeal an INC, and so and expect that an INC is less likely to be rescinded when there are more inspectors conducting the inspection. Using the sample of inspections that

TABLE XIII

Number of Inspectors on Outcome of INC

| | Rescinded | | Civil Penalty | |
|---|---|---|---|---|
| | (1) OLS | (2) IV | (3) OLS | (4) IV |
| No. Inspectors | -.0020 | .0283 | .0037 | .3214* |
| | (.0120) | (.0997) | (.0242) | (.1915) |
| Full Controls | Yes | Yes | Yes | Yes |
| n | 758 | 758 | 758 | 758 |
| Mean of Dep. Var. | .03034 | .03034 | .06860 | .06860 |
| First Stage F-stat. | | 6.57147 | | 6.57147 |

*Notes:* Sample includes inspections that resulted in an INC. Dependent variable is whether one or more INCs were rescinded or sent for civil penalty review. Controls also include all covariates found in Table VI. *** Statistically significant at the 1% level; ** 5% level; * 10% level. Robust standard errors shown in parentheses clustered by operator (91 operators).

resulted in INCs, we examine whether they are less likely to be rescinded with more inspectors conducting the inspection. The first two columns of Table XIII report the OLS and IV coefficients in a regression of the number of INCs that were rescinded on the number of inspectors. The sample only includes inspections that received INCs, and therefore the instrument is not as strong as before. In both cases, we do not find an effect with more inspectors.

INCs can also be submitted for civil penalty review.[28] The paid civil penalties have ranged from $800 to 810,000$. [29] Following our finding that more inspectors result in more stringent INCs, we also would expect that more INCs would also be submitted for civil penalty review; we find that the inspections that have more inspectors due to weather weakly significantly more likely to have the INCs sent for civil penalty review (fourth column of Table XIII).

We do not see that repeat visits result in more, or less, INCs that are rescinded or sent to civil penalty review (Table XIV).

### A.2. *Example from the Possible Incident of Non-Compliance (PINC) list*

In the PINC list, there are guidelines governing many aspects of oil and gas operations including testing and checking specific components' functionality, personnel training, record-keeping, drilling operations, and oil spill response plans. Below is an example of a general environmental protection guideline listed in the PINC list.[30]

[28]INCs must be submitted for civil penalty review if the violations are not corrected within a designated period of time or if the violations cause or could cause a threat of serious, irreparable, or immediate harm or damage to life, property, or the environment. See http://www.bsee.gov/Inspection-and-Enforcement/Civil-Penalties-and-Appeals/Civil-Penalties-Assessments-and-Appeals.aspx.

[29]A list of the civil penalties paid can be found at: http://www.bsee.gov/Inspection-and-Enforcement/Civil-Penalties-and-Appeals/Civil-Penalties-and-Appeals.aspx

[30]For the full list of PINCs, see:
http://bsee.gov/uploadedFiles/BSEE/Enforcement/Inspection_Programs/OFFICEPINCLIST_JBA

*Does the operator ensure activities authorized in this part are carried out in a manner that provides for protection of the environment?*

*Inspection procedure:*

*Visually check the waters surrounding the facility when en route to, approaching, departing, or passing a facility by boat, helicopter, or fixed wing aircraft. Look for sheens, slicks, wastes, and other pollutants originating from the facility, risers, or pipelines. During the facility inspection, check the water for signs of any pollutants.*

*If noncompliance exisits*

- *Issue a warning (W) INC if:*

  *The cause of the discharge has been identified and corrected prior to the inspection or observation, and no further pollution is occurring.*

- *Issue a component shut-in (C) INC if:*

  *A specific component has been determined to be the cause of pollution and the pollution is ongoing at the time of the inspection or observation.*

- *Issue a facility shut-in (S) INC if:*

  *More than one specific component has been determined to be the cause of the pollution and the pollution is ongoing at the time of the inspection or observation.*

The PINCs outline the enforcement actions to be taken upon different degrees of non-compliance. The inspector *must* take these actions, however one might imagine that there could be circumstances where the interpretation of the definition of a specific component or the timing of the incident, might vary the enforcement action taken.

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## TABLE XIV

### Impact of Repeat Visits on Recinding and Civil Penalty Review

| | (1) Recinded | (2) Civil Penalty |
|---|---|---|
| Lake Jackson × Post Closure | .008*** | .002 |
| | (.003) | (.006) |
| Lake Jackson | -.005** | .005 |
| | (.002) | (.005) |
| Post Airport Closure | | |
| | | |
| Controls | Yes | Yes |
| n | 32,442 | 32,442 |
| Mean of Dep. Var. | .007 | .012 |

*Notes:* Sample includes inspections that resulted in an INC. Dependent variable is whether one or more INCs were rescinded or sent for civil penalty review. Controls also include all covariates found in Table VI. *** Statistically significant at the 1% level; ** 5% level; * 10% level.