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RESOURCES FOR THE FUTURE

THE IMPACT OF TEAM INSPECTIONS ON ENFORCEMENT AND DETERRENCE

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This paper provides new insights into the productivity of teams. Government enforcement agencies often send teams of inspectors instead of a sole inspector to a regulated facility. Yet, determining the impact of teams is problematic due to endogeneity (e.g., the enforcement agency might naturally send larger teams when they expect a more violations). Exploiting exogenous variation in the number of inspectors that are sent to offshore oil and gas platforms in the Gulf of Mexico, we show that adding an inspector to a team increases the number of sanctions issued as well as the severity of the sanctions.

Keywords: inspections, enforcement, deterrence, offshore oil

JEL: Q58, K42.

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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, 2009, for a review). Much of the empirical literature on crime has focused on the incentives and behavior of *potential offenders*. Examples include studies of the effect that increasing the probability of detection has on deterring non-compliance, such as by increasing police on the street (Corman and Mocan, 2000; Di Tella and Schargrodsky, 2004), referees on a basketball court (McCormick and Tollison, 1984), inspections of oil transport vessels (Epple and Visscher, 1984; Cohen, 1987; Grau and Groves, 1997; Gawande and Wheeler, 1999), or inspections of industrial facilities (Magat and Viscusi, 1990; Laplante and Rilstone, 1996; Gray and Deily, 1996; Helland, 1998; Earnhart, 2004; Cohen, 1999; Gray and Shimshack, 2011). Separate from the deterrent effect from increasing the probability of detection, the other side of the coin examines the deterrent effect of increasing sanction severity, such as imprisonment (Drago et al., 2009; Levitt, 1998) or monetary 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 on (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.[1] To our knowledge, all of the previous studies on incentives and behavior of enforcers are based on individual behavior and not group behavior.[2] Yet, in many cases enforcement agencies send teams of enforcers, often with the expressed goal of minimizing corruption (Klitgaard, 1988).

Inspections are the primary mechanism to insure food, drug, worker, and environmental

[1]For example, see "Internal Audits Reveal Federal Enforcement Lapses," *Energy and Environment Daily*, April 18, 2011 on the Mine Safety and Health Administration (MSHA) and Tom Zeller, Jr., "Nuclear Agency Is Criticized as Too Close to Its Industry," *New York Times*, May 7, 2011.

[2]A related literature has examined the impact of increasing the number of basketball referees from two to three showing that the accuracy of officiating improves and deters violators McCormick and Tollison (1984). 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 effect, and are not focused on the behavior of the enforcer.

safety across a multitude of industries, however, the regulatory agencies performing inspections are budget constrained. Understanding the impact that group size has on inspection outcomes is useful for regulatory agencies with limited resources. A regulator might be able to increase enforcement by reallocating between the number of inspectors and the number of inspections. The aim of the present paper is to study the effect that adding an additional inspector to an inspection team has on the types of sanctions issued well as the subsequent deterrence of violations at the inspection site. We provide new insights by examining data on inspections of offshore production facilities in the Gulf of Mexico.

Two key difficulties we must overcome as we investigate the effect of group size 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). Therefore we use a random assignment of inspector group size, which is driven by weather-inflicted restrictions, to identify a causal effect of group size on enforcement outcomes. 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. In the case that one airport serves a large area, it is possible that bad weather only afflicts part of the inspection area, while the remainder of the area is still accessible. When this happens in the Gulf, inspection plans are modified at the last minute, and more inspectors are sent on fewer inspections.[3]

We find that increasing the number of inspectors in an inspection team results in a larger number of severe sanctions, indicating that enforcement would be increased by adding manpower to inspections. The increase in severity from an additional inspector is larger than the average sanction from a typical inspection, implying that severity can be increased by reallocating from the number of inspections to the number of inspectors. We then use this variation in severity to examine the effect on future safety outcomes.[4] We find large, but

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

[4]Apart from the broad literature on the effects of environmental enforcement on deterrence, there is also a broad literature on determinants of safety, including, for example, the effect of OSHA regulations on workplace safety (Viscusi, 1986), market restructuring on nuclear safety (Hausman, Forthcoming), or

statistically insignificant, reductions in incidents, such as oil spills, explosions, injuries and fatalities, occurring in the short term (six and twelve months) after a platform was inspected by a team with more inspectors. The statistical insignificance of our findings could be driven by the sanctions simply not being stringent enough (as was proclaimed after the BP Deepwater Horizon spill by the director of the regulatory agency Bromwich, 2010).[5] However, the imprecise coefficients are most likely to be driven by the low statistical power of these infrequent events.

Most studies on the deterrent effect of inspections and enforcement have focused on the extensive margin, i.e., measuring the effect of the frequency of inspections (see Gray and Shimshack, 2011, or Shimshack, 2014, for thorough reviews). Less attention has been given to the effect of inspection intensity. The investigation of the effects of increased inspection intensity is equally important for the design of optimal inspection policy. Several studies have examined various effects that might arise from a group setting. On one hand, teams may be more productive than individuals (Hamilton et al., 2003). On the other hand, teams could be less productive because of opportunities to free-ride (Alchian and Demsetz, 1972). Moreover, peer pressure within a group might influence members of the team to conform to the group norm (Kandel and Lazear, 1992). At the extreme, groupthink can result in a collective, willful blindness of bad news.[6]

This paper also relates to the literature on corruption and rent-seeking. Becker and Stigler (1974) noted that both criminal and regulatory offenders who face punishment for their violations have an incentive to try to influence the enforcer. 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 en-

profitability in the airline industry (Rose, 1990).

[5]A finding that ex-ante compliance inspections do not deter spills is also consistent with research on oil spills from tanker ships (Cohen, 1987; Anderson and Talley, 1995).

[6]See (Bénabou, 2013) for a theoretical model of overconfidence and denial, motivated by the Columbia space shuttle disaster.

forcer 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. Jin and Lee (2011) find evidence of collusive behavior between inspectors and restaurants. These previous studies examine the relationship between an individual inspector and the inspected party. However, as the number of inspectors increases, so does the cost of influencing their decisions. Thus, we expect an increase in the number of inspectors to partly mitigate the ability to influence their behavior. While our empirical context is the enforcement of safety regulations in the Gulf of Mexico, the implications of our findings are likely to carry over to most government enforcement activities facing resource constraints.

The paper is organized as follows. In the next section we provide background information on inspections in the Gulf of Mexico and discuss theoretical implications for optimal inspection policy. Section 3 lays out our identification strategy to examine the impact of inspector group size on enforcement and incidents. In Section 4 we describe our data and provide some summary statistics. In Section 5 we discuss our main results. Section 6 summarizes and draws some policy conclusions.

2. BACKGROUND

2.1. *Inspections in the Gulf of Mexico*

Inspecting offshore oil and gas production platforms (also termed facilities) is a costly endeavor. In 2010, the offshore oil and gas regulator's budget to conduct inspections was $23 million.[7] However, there are over 3,000 offshore production platforms in the Gulf of Mexico

[7] The regulator was restructured after the BP oil spill, and its name changed twice. Formerly, the Minerals Management Service (MMS), it became the Bureau of Ocean Energy Management (BOEMRE) in 2010.

alone, which must be inspected at least once every year.[8] As of 2011, these inspections were carried out by a staff of only approximately 55 inspectors. After the BP Deepwater Horizon spill in 2010, it was widely recognized that the enforcement agency was underfunded, and in 2012, the total budget for the regulator doubled to $50 million, with the call to "hire new oil and gas inspectors."[9]

Inspectors perform various inspections, not only of the production platforms discussed here, but also of mobile offshore drilling units (such as the Deepwater Horizon drilling rig), meters measuring oil and gas flows, and pipelines. To unify the type of inspection examined in this study, we focus on the annual "production" inspections of platforms.[10] Production inspections are required for all platforms at least once annually for compliance with safety regulations, accurate recordkeeping, and proper maintenance. The primary goal of the production 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-Compliance (PINC) list.[11]

Figure 1 depicts the location of the offshore oil and gas platforms across the six different districts in the Gulf (Corpus Christi, Houma, Lafayette, Lake Charles, Lake Jackson, and New Orleans). Inspector groups travel to the platforms using helicopters which are stationed at the district airports, indicated by the stars in Figure 1. An inspection group can range from one to six inspectors. The assignment of inspectors to platforms is not random. The lead inspector prints out a list of facilities that are due for inspection within the next four to six weeks. The lead inspector can assign specific inspectors to inspectors, however, in most cases the inspection forms are put in the bullpen for inspectors and they select the facility

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Then in 2011 BOEMRE was split into two agencies, Bureau of Ocean Energy Management (BOEM) with the responsibility of planning and leasing, and the Bureau of Safety and Environmental Enforcement (BSEE) having responsibility for compliance inspections. Thus the data analyzed in this paper will be attributed to BSEE, however at the time of the inspections the agency was called MMS.

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

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

[10] Note that nevertheless, we use data from all types of inspections in constructing variables on the inspection history of inspectors.

[11] An example from this list is shown in Appendix A.

or area that they want to inspect. The lead inspector ensures that the same inspector is not assigned to the same facility in consecutive years. Once the daily inspection schedule is finalized, the lead inspector assigns a helicopter to each inspector and the inspectors proceed to the heliport.

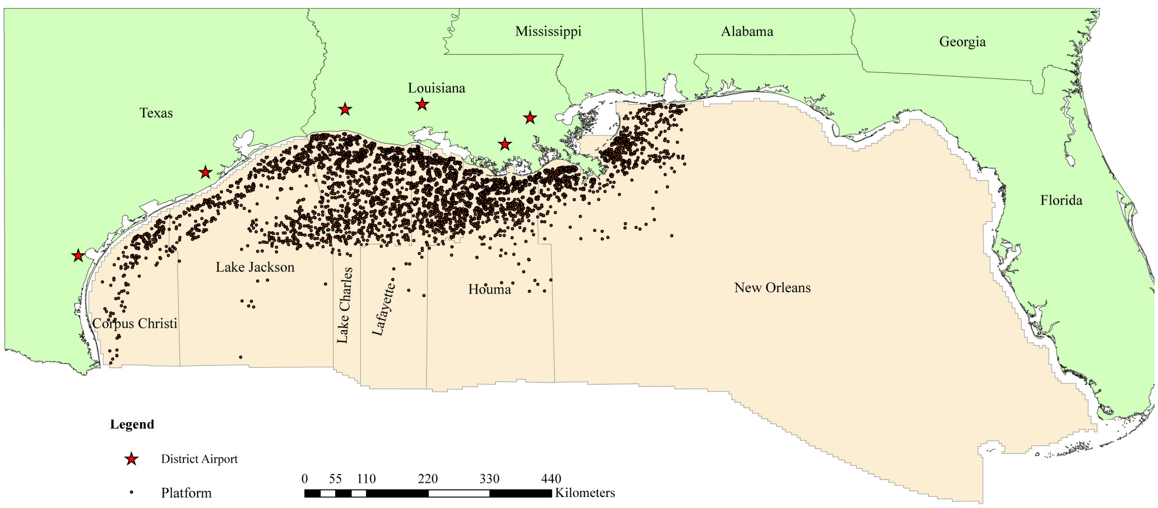
A typical inspection unfolds in the following way: in approaching the platform with a helicopter, the inspector looks at the surrounding water for pollution, any drilling, or vent gas.[12] Upon landing, the inspector walks around the platform to check its general condition, while reviewing the PINC list to determine whether violations are occurring. After the walk-around, the inspector starts a review of paperwork. If there is more than one inspector in the group, one inspector reviews paperwork while any other inspectors 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.

Upon detection of a violation or specific safety equipment failure inspectors issue "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, or component, 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. Any violations are written on the inspection form, and the INCs are written and given to the company representative, who reads the INC and is asked whether 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 group then returns to the district office. A different inspector in the district office verifies the data. The file clerk forwards completed inspection forms to the supervisory inspector for his or her review. Inspectors are not required to meet INC quotas.

[12] Our information on inspector assignment and inspection protocol comes from an internal document, Offshore Energy and Minerals Management (2009).

While the bulk of enforcement actions result in the less severe INCs, warnings and component shut-ins, about 2.4 percent of all production inspections result in a facility shut-in—which could amount to millions of dollars annually in costs to the industry. Office of Inspector General, Department of the Interior (2010a) estimates that a facility shut-in costs a large production platform over $900,000 a day.

Figure 1: Districts, Platforms, and District Airports in the Gulf of Mexico.



2.2. *The Importance of Helicopter Flying Conditions and District Size*

Since the inspection of offshore production platforms relies on the ability of helicopters to transport inspectors to and from platforms, weather conditions may disrupt normal inspection schedules. Flights 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). On average, bad weather results in inspectors only being able to fly 80 percent of the time (Offshore Energy and Minerals Management, 2009). However, there are also occasions when bad weather is localized in one part of the district and therefore does not prevent all inspections from occurring, but rather only the platforms affected by the bad weather. Because the day's inspections are decided at the inspections office, before the inspectors leave for the airport, once inspectors reach the airport, weather may preclude some of the day's platforms from being inspected while leaving other platforms accessible. 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" and sent to platforms that are accessible.[13] Therefore, times when weather prevents flying to only a part of the inspection district, while leaving another part unaffected, provides an exogenous increase in the number of inspectors while not influencing other conditions at the platforms that are inspected.[14]

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 weather that some of the planned inspections of the day would not be feasible. As shown in Figure 1, the New Orleans district covers the largest area in the Gulf of Mexico, however, drilling restrictions off the coast of Florida have resulted in platforms not being spread across the whole district. On October 1, 2003, the Corpus Christi inspections office was closed, and all inspections for both Corpus Christi and Lake Jackson started to originate from the Lake Jackson airport. Therefore, after October 2003, Lake Jackson district became the district with the most dispersed platforms in the Gulf of Mexico and effectively the largest district. For this reason, we focus on Lake Jackson after the closure of the airport in Corpus Christi, as we expect that weather becomes a more important determinant of inspection group size in the Lake Jackson district.

[13] Personal communication with a lead inspector.

[14] In principle, inspectors could also be allocated to brand new inspections. However, most offshore inspections are announced so that inspectors are ensured that a helicopter landing pad will be available. In our data 99.9 percent of inspections are announced and we do not see an increase in unannounced inspections when weather conditions are bad, suggesting that inspectors are added to already announced inspections.

2.3. *Theoretical Implications*

There are several potential mechanisms through which increasing inspector group size might increase the intensity of inspections. More inspectors means that there are more eyes available to find violations—hence, we would expect an increase in issued sanctions when more inspectors arrive at a given platform. If inspections are typically understaffed, then with more inspectors we would expect to see an increase of *all* types of enforcement actions (i.e., more warnings, component shut-ins and facility shut-ins). Yet, it is unclear whether there will be a shift in the severity. Understaffing might lead to a focus on the major, most important issues or alternatively, might lead to a focus on only the minor, easily-managed issues.

Group size also changes other aspects of the inspection. For example, another channel by which more inspectors would matter arises because it would be harder to capture the inspectors, simply because there are more inspectors to capture. An inspector would have to exert more effort to issue an INC if an operator protests its issuance. In fact, there is anecdotal evidence that enforcement staff are subject to industry pressure. For example, after the BP Deepwater Horizon oil spill, an internal government 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, 2010b). The National Commission on the BP Deepwater Horizon Oil Spill even cited an instance where an inspector was in the process of negotiating an employment opportunity during the same time period he was inspecting his future employers platforms (Graham et al., 2011).[15] But regulatory capture could also be driven by more subtle forms of pressure. For example, facility personnel are said to have made comments such as "there goes my bonus" or "my wife is sick, and I'll lose my job," to deter inspectors from issuing violations (Office of Inspector General, Department of the Interior, 2010). 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

[15] 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 driving regulatory capture.

group present, the inspectors might be better able to avoid pressure and hence be more likely to write up the INC or to write up a more severe INC.

3. EMPIRICAL STRATEGY

We are interested in whether increasing the number of inspectors conducting an inspection has an effect on the resulting enforcement actions as well as on the subsequent safety at the platform. We start by running ordinary least squares (OLS) regressions of the following type:

$$y_{it} = \varphi + \vartheta \text{Inspectors}_{it} + \mu_t + \upsilon_o + \mathbf{X}_{it}\varrho + \varepsilon_{it} \tag{1}$$

where i denotes the inspection and Inspectors_{it} is the number of inspectors that conducted the inspection of a platform at time t. We include year-month fixed effects, μ_t to control for district-wide changes over time, and operator fixed effects, υ_o, to account for any time-constant unobserved characteristics of the operator. We also include controls for the platform, inspector, and operator in $\mathbf{X}_{it}$. Platform characteristics include age, distance to shore, water depth, production (in the month prior to the inspection), an indicator for whether the platform is a major complex, whether it is manned 24 hours a day, and the number of wells at the platform at the time of the inspection. Inspector characteristics include an indicator for whether one of the inspectors is new and the total number of inspections conducted in the past 5 years. 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 time varying and measured at the time of the inspection. We also include an indicator for whether the inspection occurred shortly after a hurricane. The term ε_{it} is a mean-zero error term, clustered at the operator level.

Our parameter of interest is ϑ, which measures the impact of an additional inspector on the outcome variable y_{it}. When examining the impact of inspector group size on enforcement, y_{it} denotes the aggregate number of INCs that inspectors write during an inspection. However, inspectors might not only change the aggregate number of INCs they write, but also the distribution of citations given; for example, they may shift from warnings to component shut-ins or from component to facility shut-ins. To investigate changes in the distribution of INCs, we break the number of INCs into subcategories 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 the offshore regulator uses to calculate an Operator Safety Index: one facility shut-in is equivalent to four warnings or two component shut-ins (Slitor, 2000). When examining the impact of inspector group size on deterrence, the outcome variable, y_{it}, is the count of the number of incidents such as oil spills, blowouts, injuries and fatalities that were reported on a platform within a set time period after the inspection ($t + m$ where m is six or twelve months).

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 ε_{it} would be positive. In this example, the OLS estimate of the effect of an additional inspector would be biased upwards. To deal with the endogeneity of the number of inspectors, we instrument for the number of inspectors using the standard deviation in wind speed on the day of the inspection (SDWIND_t) across the Lake Jackson district after the closure of the airport in Corpus Christi.[16] A high SDWIND indicates that there are areas of the district with high winds and areas with low winds; i.e., areas that cannot be accessed and areas that can be accessed (and therefore also receive the inspectors that were originally scheduled to the inaccessible areas).

Because larger inspection groups are sent when SDWIND is high, 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).[17] The instrument

[16]We later demonstrate that wind speed near the inspected platforms does not have an effect on the number of inspectors or the enforcement outcomes.

[17]Note that the LATE is not necessarily equal to the average treatment effect. The LATE represents a weighted average response of those platforms that had a change in inspector group size because of weather,

satisfies the three assumptions in estimating a LATE. First, the monotonicity assumption requires that variation in wind speed would not result in fewer inspectors being sent to a platform. This assumption is likely to hold in our case: if SDWIND is low, there are either no inspections because the weather is bad everywhere, or fewer inspectors per inspection, because the weather is good in all areas. If SDWIND is high, there are more inspectors per inspection because the weather is good in one area and bad in another. A second assumption for the LATE is that the instrument is as a good as randomly assigned and thus independent of treatment status. This assumption would be violated if platforms that are inspected when variation in wind speed is high systematically differ from the platforms that are inspected when variation in wind speed is low. In the empirical analysis we will shed light on this concern by investigating the effect of variation in wind speed on characteristics of inspected platforms. A final assumption for measuring the LATE is that variation in wind speed affects enforcement actions only through inspector group size (exclusion restriction). 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 larger number of violations than otherwise would have occurred under normal wind speeds. This is unlikely to be the case because 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, in the empirical analysis we will find that different measures of weather (mean wind speed across the district on the day of the inspection, wind speed closest to the platform, and mean wave height across the district) do not determine the number of enforcement actions.

Under these assumptions, we can estimate the following first-stage equation that models the relationship between wind speed and the number of inspectors:

$$\text{Inspectors}_{it} = \alpha + \beta \text{SDWIND}_t + \mathbf{X}_{it}\gamma + \mu_t + \upsilon_o + \varepsilon_{it}, \tag{2}$$

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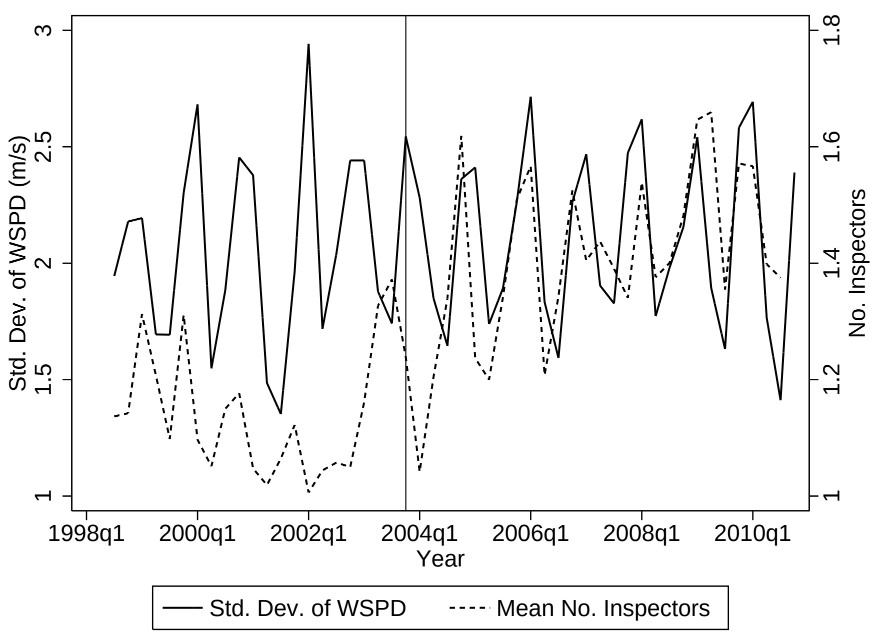
where the weight is proportional to the number of platforms that get an additional inspector (Imbens and Angrist, 1994; Angrist and Imbens, 1995). The LATE does not tell us about the effect of an additional inspector on those platforms that would not get an additional inspector even in bad weather.

where SDWIND_t is the standard deviation in wind speed across the Lake Jackson district at 8:00 a.m. on the day the inspection takes place.

Support for our first-stage equation is provided in Figure 2, which shows quarterly averages of the standard deviation in wind speed at 8:00 a.m. and 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; this is particularly pronounced after inspectors had to cover a larger geographical area. After the closure of the Corpus Christi office in 2003, the average number of inspectors in Corpus Christi and Lake Jackson is more closely correlated with the standard deviation in wind speed across the district (the mechanism is described in Section 2.2).

Figure 2: Instrumenting for the Number of Inspectors with Variation in Wind Speed



Notes: Quarterly data obtained by averaging the 8:00 a.m. standard deviation of wind speed across five buoys in Corpus Christi and Lake Jackson. Vertical line indicates when Corpus Christi was incorporated into the Lake Jackson district.

Figure 2 indicates a seasonal pattern illustrated by spikes in standard deviation of wind speed during the winter and dips during the late summer. However, seasonality is not the driving force behind the relationship between wind speed and inspector group size. Figure 3 in Appendix B shows a scatter plot of the deseasonalized standard deviation of daily wind speed and average inspector group size per day before (Panel A) and after (Panel B) the closure of Corpus Christi airport. Consistent with Figure 2, there is no relationship between standard deviation of wind speed and inspector group size prior to the closure of the Corpus Christi airport, while after the closure standard deviation in wind speed has significant predictive power for inspector group size.[18]

4. DATA AND SAMPLE CONSTRUCTION

4.1. *Data*

For our analysis we combine data from several sources. Records of inspections were provided by the Bureau of Safety and Environmental Enforcement (BSEE). The dataset contains information on every inspection conducted in the Gulf of Mexico and includes information on the count and type of enforcement actions (INCs) taken. The dataset also contains the full names of the inspectors conducting the inspection. This information is used to calculate the number of times an inspector visited the platform in the past five years prior to the inspection, which captures the familiarity an inspector has with a particular platform. We also calculate the number of enforcement actions that a platform received in the past. We construct these variables using the full dataset dating back to 1986. BSEE also provided us with a dataset containing all serious accidents, fatalities, injuries, explosions, and fires. Incidents include fires, explosions, blowouts, loss of well control underground and at the surface, collisions, spills of oil or drilling fluids, equipment failure, injuries, and fatalities. In the analysis we examine all incidents together, and then only injuries and fatalities.[19] The regulations for incident reporting were made more stringent on July 17, 2006, when operators were 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

[18] We also control for seasonality in our main regression specifications by including year-month fixed effects.

[19] 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, but nonetheless, incidents are self-reported by platforms and there is potentially under reporting.

to an evacuation or days away from work, or property damage exceeding $25,000).[20]

Two datasets containing platform characteristics from the Bureau of Ocean Energy Management (BOEM) were used to create a panel of every platform in the Gulf of Mexico from the year the platform was first installed through 2010.[21] The data contain information on the distance to shore, water depth, lease number, whether there are personnel on board 24 hours a day, and whether the platform is considered to be a "major complex."[22] Production data for all wells in the Gulf of Mexico from 1996 to 2010 were also obtained online from BOEM.[23] The data contain a unique well identifier (the API well number), monthly volume of oil and gas produced, and days on production. Using another dataset available from BOEM on well characteristics, we assigned a platform identifier to the API well numbers so that we could aggregate the monthly well production to monthly platform production.[24] Using the date that the wells were drilled we created a variable for the number of wells at each platform at the time of the inspection.

Data on the ownership of the lease and the designated operator of a lease were obtained online from BOEM.[25] These data contain the working interest of all owners of Gulf leases, including all ownership changes from the assignment date 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 of the working interest of the lease. At any one point in time, however, there is only one designated operator of the lease. The operator, as defined by BOEM, is either the leaseholder or the party designated (and approved) to operate a portion of a given lease.[26] A record of platform operators (received from BOEM) was used to determine

[20] 30 CFR Part 250, Final Rule (FR 19640), Minerals Management Service, Department of the Interior.

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

[22] Major complex is defined as a platform that has at least one structure with at least six completions or two pieces of production equipment

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

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

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

[26] 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.

the operator of a platform at the time of the inspection. BOEM 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 BOEM. For the remainder of unmatched observations, the parent company found in BOEM's operator safety summaries 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.

Finally, 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.[27] There are many NDBC deployed buoys spread throughout the Gulf of Mexico. Unfortunately, only a handful of these provide daily data spanning the dates studied. In the case of the Lake Jackson district we have data for our time period from five buoys. However, this is a large number compared to the number of buoys available in other districts. All inspections conducted on day t are assigned the same SDWIND, which is constructed as the standard deviation across the five buoys at 8:00 a.m. on day t. 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).[28]

[27] Although visibility, cloud ceiling, and the presence of lightning also determine whether flying is an option, it is not possible to obtain these data over the Gulf of Mexico, and our estimation strategy depends on distinguishing weather across the district.

[28] 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).

4.2. *Sample Construction*

Our sample consists of all production inspections of offshore platforms in Lake Jackson after it subsumed the Corpus Christi subdistrict in October 2003 until September 2010. 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 1 for a map of the Gulf). Without many platforms spread across a large area, bad weather would be more likely to 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. Moreover, Lake Jackson has the largest number of buoys that provide weather data on a daily basis since 2003. However, to examine the robustness of our results, we will also estimate equation 1 using inspections data from all districts in the Gulf of Mexico.

We focus on annual production inspections, which account for 81 percent of the 13 different types of facility inspections. We restrict the sample to only include these inspections because they are more uniform in how they are conducted and in the type of INCs issued. Nevertheless, to ensure we construct the variables indicating a particular inspector's history correctly, we include data on 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 in the past five years (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.

Table I reports summary statistics for production platform inspections in Lake Jackson between October 2003 and September 2010. As shown, while warnings and component shut-ins are relatively common and occur in 25.7 percent and 21.9 percent of the inspections, respectively, facility shut-ins occur only in 2.6 percent of inspections. Incidents such as spills or accidents occur in 8.3 percent of the time during the 12 months following a production inspection. Importantly, while the mean of our instrument for group size, SDWIND, is 1.89 m/s, there is substantial variation across time: the standard deviation of SDWIND is 0.923 and the minimum and maximum values are 0.269 m/s and 6.29 m/s, respectively.

TABLE I
Summary Statistics

	Mean	Std. Dev.	Min.	Max.
A. Outcome Variables				
% Non-zero Warnings	25.7	43.7	0	100
No. Warnings	.455	1.04	0	10
% Non-zero Component Shut-ins	21.9	41.3	0	100
No. Component Shut-ins	.483	1.35	0	16
% Non-zero Facility Shut-ins	2.6	16.0	0	100
No. Facility Shut-ins	.0339	.242	0	5
% Non-zero Weighted INCs	37.7	48.5	0	100
Weighted INCs	1.56	3.6	0	42
% Non-zero Incidents 12 Mo. After	8.3	27.6	0	100
No. Incidents 12 Mo. After	.109	.414	0	6
% Non-zero Injuries & Fatalities 12 Mo. After	.747	8.6	0	100
No. Injuries & Fatalities 12 Mo. After	.0115	.149	0	3
B. Weather Variables				
SDWSPD (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)	.121	.326	0	1
No. Inspectors	1.36	.608	1	6
Time Since Last Insp. (days)	342	128	2	1,139
C. Inspector Characteristics				
New Inspector (Indicator)	.0309	.173	0	1
Inspections by I, past 5 yrs	335	193	5	852
Cum. Inspections of P by I, past 5 yrs	.598	.872	0	7
D. 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)	.0356	.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
Inactive (Indicator)	.26	.439	0	1
E. 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	2,008			

Notes: Sample includes production inspections on offshore facilities in Lake Jackson/Corpus Christi October 2003 to September 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.

5. RESULTS

5.1. *Descriptive Evidence*

We start by presenting some descriptive evidence on the impact of inspector group size on enforcement and deterrence. Table II reports various summary statistics of the outcome variables by the number of inspectors conducting the inspection. Several things can be observed from the table. First, there is a positive correlation between the number of inspectors and the percent of non-zero enforcement actions. For example, the probability of a component shut-in increases from 19.6 to 25.0 percent when moving from one to two inspectors, and increases further to 33.7 percent with three inspectors and 57.1 percent with four or more.

Second, the mean of non-zero INCs is generally increasing with the number of inspectors conducting the inspection, although the increase is less pronounced compared to the probability of an INC. This pattern suggests that more inspectors increase the inspection intensity primarily along the "extensive margin," i.e. the probability of an INC, and less along the "intensive margin," i.e. the mean of non-zero INCs. Third, the impact an additional inspector on enforcement actions appears to be non-linear. In particular, the impact of an additional inspector is always smaller when moving from one to two inspectors compared to the effect when moving from three to four inspectors. We examine the non-linearity in more detail in the next section.

Fourth, these numbers do not capture the causal impact of group size on enforcement but may reflect that more inspectors are sent to platforms that are thought to be poor performers. Consistent with this view, there is a positive association between the number of inspectors and percent of non-zero incidents and injuries or fatalities occurring. For example, the probability of any incident occurring 12 months after an inspection increases from 7.5 to 8.8 percent when a second inspector is added and increases further to 14.6 percent with three inspectors and 28.6 percent with four or more. We therefore rely on variation in weather across the Lake Jackson/Corpus Christi district after the closure of the airport to provide us with variation in the number of inspectors that is independent of unobservable platform characteristics.

TABLE II

Summary Statistics by Number of Inspectors

	(1) One	(2) Two	(3) Three	(4) Four+
A. Warnings				
% Non-zero	24.9	25.9	36.0	35.7
mean of Non-zeros	1.76	1.73	2.06	2.00
S.D. of Non-zeros	1.28	1.46	1.70	1.00
B. Component Shut-ins				
% Non-zero	19.6	25.0	33.7	57.1
Mean of Non-zeros	2.13	2.11	3.33	2.13
S.D. of Non-zeros	2.04	2.04	3.19	1.36
C. Facility Shut-ins				
% Non-zero	1.5	4.3	10.1	7.1
mean of Non-zeros	1.38	1.14	1.44	1.00
S.D. of Non-zeros	1.07	.47	.73	-
D. Weighted INCs				
% Non-zero	35.2	41.1	53.9	64.3
Mean of Non-zeros	3.86	4.13	6.63	5.33
S.D. of Non-zeros	4.51	4.91	7.25	4.80
E. Incidents 12 Mo. After				
% Non-zero	7.5	8.8	14.6	28.6
Mean of Non-zeros	1.25	1.42	1.46	1.00
S.D. of Non-zeros	.60	.92	.78	.00
F. Injuries & Fatalities 12 Mo. After				
% Non-zero	.6	.8	2.3	0
Mean of Non-zeros	1.22	2.50	1.00	-
S.D. of Non-zeros	.44	1.00	.00	-
Observations	1,396	509	89	14

Notes: Sample includes production inspections in Lake Jackson October 2003 to September 2010. Statistics include the percent of non-zero observations (% non-zero), the mean of non-zero observations (mean non-zeros), and the standard deviations of non-zero observations (S.D. non-zeros). There is only one observation with six inspectors, and none with five.

5.2. *Main Results*

Table III reports the first stage relationship between inspectors and the standard deviation in wind speed in the instrumental variables estimation. The specification in column 1 only includes year-month fixed effects, the specification in column 2 also adds operator fixed effects, and the specification in column 3 adds all exogenous variables described in detail in section 3. For our purposes, the important finding is that the number of inspectors is positively related to wind speed variability. Independent of the specification, we find a strong first stage relationship; parameter estimates are statistically significant and remarkably similar regardless of whether we use additional covariates. Figure 3 in Appendix B provides a visual illustration of the first stage, showing the fact that following the airport closure at Corpus Christi, the average number of inspectors per inspection was positively correlated with the standard deviation of wind speed. All specifications also pass the weak instrument test given that the F-statistics are larger than the threshold value of 10 (Stock and Staiger, 1997).

As a first placebo test, we use the standard deviation in wind speed exactly 365 days before the inspection as the instrumental variable (column 4). In this case, the coefficient on the standard deviation is insignificant in the first stage regression, the F-statistic for a weak instrument is 1.23, and all coefficients in the second stage are insignificant. Furthermore, using the standard deviation in wind speed the day before (column 5) *and* the day after the inspection (column 6) results in a first stage F-statistic of 0.14 and 0.26, respectively, and all affected coefficients are insignificant. Additionally, consistent with Figure 3 in Appendix B, columns 7-9 indicate that there is no first stage relationship between standard deviation in wind speed and inspector group size before the closure of Corpus Christi airport. This finding supports the claim that for standard deviation of wind speed to have an impact on inspector group size, we need a large enough geographical area.

TABLE III

First Stage: Number of Inspectors

	Main estimates Post airport closure			Placebo tests Post airport closure			Placebo tests Pre airport closure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Std. Dev. of WSPD on inspection day	.061**	.057**	.062***				.001	.004	.003
	(.024)	(.026)	(.023)				(.010)	(.010)	(.011)
Std. Dev. of WSPD one year before				-.016					
				(.015)					
Std. Dev. of WSPD one day before					.004				
					(.011)				
Std. Dev. of WSPD one day after						-.005			
						(.017)			
Year-Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Operator Effects	No	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes	No	No	Yes
n	2,008	2,008	2,008	2,008	2,008	2,008	1,721	1,721	1,721
Mean of Dep. Var.	1.364	1.364	1.364	1.364	1.364	1.364	1.147	1.147	1.147
R^2	.114	.174	.263	.258	.257	.257	.134	.225	.434
First Stage F-stat.	13.19	11.07	14.48	1.27	.06	.08	.08	.08	.08

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 77 operators). Controls include platform's age, distance to shore, water depth, previous month's production, count of wells, operator's number of leases, platforms and working interest, inspector's count of past inspections, indicators for whether the platform is inactive, a major complex, manned-24 hours, was in Corpus Christi, and whether the inspection was unannounced, conducted by a new inspector, or occurred after a Hurricane. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table IV reports on our main regression results relating the number of inspectors to the resulting enforcement actions. This table shows both OLS and IV results when including the full set of control variables, but the results are similar for specifications that only include year-month fixed effects or year-month and operator fixed effects.[29] The OLS estimates indicate that adding an additional inspector has no significant effect on the number of warnings issued, but leads to a significant increase in component shut-ins, facility shut-ins, and the weighted combination of enforcement actions. While these estimates are based on data from Lake Jackson district, Table IX in Appendix C shows that the OLS estimates using data from all districts in the Gulf of Mexico are similar. The IV estimates are larger in magnitude than the OLS estimates, but they are also less precisely estimated. As a consequence, in the IV estimation only the most stringent enforcement actions, facility shut-ins, are statistically significantly more likely to occur with more inspectors. The point estimate indicates that adding an inspector increases the number of facility shut-ins by .252.

We also examine whether more inspectors increase the probability of an enforcement action (Table XIII in Appendix E). The OLS estimates indicate that an additional inspector increases the probability of a component shut-in, a facility shut-in, and a weighted INC, while the IV estimates reveal only a significant increase in the probability of a facility shut-in. These estimates suggest that the overall increase in enforcement actions documented in Table IV is partly driven by an extensive margin response, i.e. more inspectors increasing the probability of an INC.

The coefficient on the number of inspectors in Table IV 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. Our data contain detailed records of the number of inspectors on the platform and therefore 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

[29] Table XV in Appendix E reports estimates for all covariates.

TABLE IV

IMPACT OF THE NUMBER OF INSPECTORS ON ENFORCEMENT ACTIONS

	Warnings		Component		Facility		Weighted	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)	OLS (7)	IV (8)
No. Inspectors	.049	.176	.211***	.516	.034**	.252**	.606***	2.216
	(.052)	(.740)	(.052)	(.620)	(.014)	(.118)	(.150)	(1.746)
Year-Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Operator Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	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
R^2	.193	.189	.215	.202	.108	.115	.219	.164
Mean of Dep. Var.	.455	.455	.483	.483	.034	.034	1.556	1.556

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 77 operators). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

speed, whereas the 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.

To examine whether there are non-linearities in the enforcement actions by inspector group size, we estimate the OLS specifications in Table IV using dummies for each level of group size instead of the count of inspectors. This approach gives us a separate coefficient on each group size level with indicators for whether the inspection had two, three, or four-or-more inspectors (Table V).[30] For each type of enforcement action, we find that the effect is largest when increasing the number of inspectors from two to three, while effects are not statistically significant when moving from one to two inspectors. The effects when moving from three to four inspectors are imprecisely estimated due to low power. In most cases, F-tests reject the null that the coefficients are equal. Therefore, it appears that the true relationship between the enforcement actions and the number of inspectors is non-linear.

Appendix D examines this issue in more detail and provides evidence that non-linearities can explain the difference between IV and OLS estimates. With higher SDWIND there are more inspections with two or three+ inspectors, however, with very high SDWIND there is a particularly large increase in the fraction of three+ inspections (shown in Figure 4 in

[30]We are not able to estimate the same specifications using IV, since doing so would require a valid instrument for each level increase in group size. However, we only have one valid instrument with limited variation.

TABLE V

Estimates at Each Level Increase in Group Size

	(1) Warnings	(2) Component	(3) Facility	(4) Weighted
Two Inspectors	-.011	.103	.013	.250
	(.047)	(.067)	(.019)	(.162)
Three Inspectors	.233	.657***	.115***	2.007***
	(.177)	(.209)	(.037)	(.471)
Four or More Inspectors	.058	.599	.029	1.373
	(.330)	(.367)	(.089)	(1.237)
Year-Month Effects	Yes	Yes	Yes	Yes
Operator Effects	Yes	Yes	Yes	Yes
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 operator (for 77 operators). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Appendix D). Therefore, the weight that the IV strategy places on a particular level shift is different than the weight that OLS places (Lochner and Moretti, 2015). Specifically, the IV weight on moving from two to three+ is larger than the OLS weight while the weight of moving from one to two is smaller than the OLS weight (Table XI). Intuitively, these weights reflect how much of the average increase in inspector group size is due to a particular level increase in group size, e.g. from two to three inspectors.

TABLE VI

Impact of the Number of Inspectors on Incidents and Fatalities and Injuries

	All Incidents				Injuries & Fatalities			
	6 Mo. After		12 Mo. After		6 Mo. After		12 Mo. After	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)	OLS (7)	IV (8)
No. Inspectors	.006	-.147	.001	-.120	.000	-.086	-.003	-.012
	(.012)	(.120)	(.021)	(.197)	(.005)	(.089)	(.007)	(.053)
Year-Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Operator Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	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
R^2	.172	.086	.242	.219	.232	.067	.322	.321
Mean of Dep. Var.	.055	.055	.109	.109	.006	.006	.011	.011

Notes: Sample includes production inspections in Lake Jackson between October 2003 and September 2010. Dependent variables are the number of incidents and injuries & fatalities within 6 months and 12 months after a inspection. In the case of the IV estimates, *No. Inspectors* is instrumented for using weather. Robust standard errors are clustered by operator (for 77 operators). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Table VI reports the estimates on the effect of inspector group size on reported incidents such as oil spills, injuries, and fatalities occurring within 6 and 12 months of any inspection.[31]

[31] Appendix E has additional tables; similar results to Table VI are found when estimating the effect of inspector group size on the probability of any incident (Table XIV) and Table XVI reports estimates for all covariates.

The first four columns report on all incidents, while the remaining columns report on a subset—only those involving injuries or deaths. As before, the table shows both OLS and IV results when including the full set of control variables. The OLS estimates are in all cases close to zero and statistically insignificant. The IV estimates are negative in all specifications and sizeable in magnitude, but the coefficients are imprecisely estimated and not statistically significant. Therefore the regressions are somewhat inconclusive because of low power, but the results weakly point to improved safety outcomes. We discuss other possible explanations for this finding in the concluding section.

5.3. *Validation of the Identifying Assumptions*

One potential concern with our instrumental variable approach is that platforms that are inspected when variation in wind speed is high systematically differ from platforms that are inspected during good weather. Such selection behavior would violate the assumption that the instrument is as good as randomly assigned. To examine this concern, we regress platform characteristics, such as the distance to the shore or the age of the platform, on the standard deviation of wind speed. As shown in Panel A of Table VII, the platforms inspected on highly variable days have the same characteristics as platforms inspected on low variation days, suggesting that this concern is unfounded.

Similarly, it is possible that variation in wind speed affects the composition of inspector characteristics. For example, it could be that "the usual" inspectors do not go on an inspection in case of bad weather, and the additional inspector is therefore less likely to be captured by a given operator. We run a number of checks to show that this concern is unfounded. More specifically, columns 1-4 in Panel B of Table VII show no significant relationship between standard deviation of wind speed and (1) the total number of inspectors on a day, (2) the probability of a new inspector on a team, (3) the experience of the team, and (4) the familiarity between inspectors and the platform. It is also not the case that the instrument is affecting operator characteristics, such as (5) the number of lessees listed on the lease, (6) the percent of working interest of the operator, and (7) firm size as proxied by the number of platforms operated by the operator.

TABLE VII

Baseline Characteristics by Standard Deviation in Wind Speed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Platform Characteristics	Dist.	Age	Prod.	INCs(t-1)	Major	Manned	Wells	Depth
Std. Dev. of WSPD (m/s)	.553	-.056	.003	.056	.001	-.019	-.214	.008
	(.731)	(.276)	(.007)	(.072)	(.013)	(.014)	(.140)	(.015)
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
R^2	.385	.410	.300	.113	.206	.273	.349	.377
Panel B: Inspector and Operator Characteristics	Total I day t	New Insp.	#Insp. by I	#Insp. of P by I	#Lessees	Working Interest	#P by O	
Std. Dev. of WSPD (m/s)	.048	-.001	4.91	-.004	.011	.005	.071	
	(.125)	(.004)	(6.87)	(.024)	(.062)	(.906)	(.719)	
Year-Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Operator Effects	No	Yes	Yes	Yes	Yes	Yes	Yes	
n	768	2,008	2,008	2,008	2,008	2,008	2,008	
R^2	.118	.218	.253	.261	.367	.428	.963	

Notes: Columns represent OLS coefficients with robust standard errors clustered by operator (for 77 operators), except for column (1) in Panel B. Dependent variables in Panel A are platform characteristics: distance to shore (1), age (2), past month's production (3), the weighted average of the INCs from the most recent prior inspection (4), whether the complex is a major complex (5), whether it is manned 24 hours a day (6), the number of wells present (7), and depth (8). Dependent variables in Panel B are inspector and operator characteristics: the total number of inspectors on day t (1), whether a new inspector was part of the team (2), the number of inspections by I in the past 5 years (3), the number of repeat visits of an inspector to the same platform in the past 5 years (4), the number of lessees (5), the percent working interest of the operator (6), and the number of platforms operated by the operator (7). Year-month and operator fixed effects included in all regressions (coefficients not reported). Sample includes production inspections in Lake Jackson October 2003 to September 2010. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

Another potential worry is that weather might be worse during high SDWIND days, and therefore SDWIND would have a direct effect on the outcome of an inspection, which would violate the exclusion restriction. We show in Table VIII 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 all have no effect on the number of inspectors or the enforcement action taken.[32] This 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. One might still worry that high variation in wind speed coincides with incidents of non-compliance issued because of damage from hurricanes. However, after a hurricane, while

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

there are fewer INCs, only the coefficient on warnings is statistically significant (see Table XV in Appendix E which shows all coefficients for all covariates in our main estimation table). This is perhaps an indication that platform operators independently undergo self-inspections for safety following a hurricane and thus are less likely to be found out of compliance when a government inspector arrives. We also note that the number of inspectors is not statistically significantly different when the inspection occurred after a hurricane.[33]

TABLE VIII

Direct Effect of Weather on Outcome of Inspection

	Inspectors			Warnings			Component			Facility		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mean WSPD	-.000			.002			.006			-.002		
	(.007)			(.014)			(.013)			(.003)		
WSPD Closest Buoy		.006			.002			.006			.000	
		(.006)			(.009)			(.011)			(.003)	
Mean Wave Height			.022			-.022			-.016			-.006
			(.046)			(.066)			(.060)			(.017)
Year-Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Operator Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	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	2,008	2,000	1,787
R^2	.255	.257	.245	.190	.191	.210	.202	.202	.205	.102	.102	.105
Mean of Dep. Var.	1.364	1.365	1.370	.455	.456	.464	.483	.484	.485	.034	.034	.035

Notes: Sample includes production inspections in Lake Jackson between October 2003 and September 2010. Dependent variables are the number of inspectors, warnings, component shut-ins, and facility shut-ins. Robust standard errors are clustered by operator (for 77operators). Controls include platform's age, distance to shore, water depth, previous month's production, count of wells, operator's number of leases, platforms and working interest, inspector's count of past inspections, indicators for whether the platform is inactive, a major complex, manned-24 hours, was in Corpus Christi, and whether the inspection was unannounced, conducted by a new inspector, or occurred after a Hurricane. *** Statistically significant at the 1% level; ** 5% level; * 10% level.

6. CONCLUDING REMARKS

There is an extensive literature on the effectiveness of increasing the frequency of inspections and/or inspection resources to improve outcomes in areas such as environmental, health and safety regulation. Yet, little attention has been given to the allocation and organization of inspection resources, resources that are often scarce across many agencies. In this paper we examine the effect that increasing the number of inspectors sent on an inspection has on enforcement outcomes and subsequent safety outcomes. While we focus on offshore oil

[33] We also tried various intervals ranging from one week to 16 weeks after a hurricane. The final specifications presented in the paper include an indicator for any inspection that occurred within eight weeks after Hurricanes Lili, Ivan, Dennis, Katrina, Rita, Gustav, and Ike.

platforms, the concern that inspectors are not being optimally employed is ubiquitous across regulatory agencies.

Given concerns of endogeneity we construct an instrumental variable based on exogenous weather-related changes in the number of inspectors sent to inspect a platform. We find strong evidence that larger inspection teams issue more severe sanctions and do so at a higher rate than what an additional inspection (consisting of fewer inspectors) would provide. Assuming that more severe sanctions are appropriate, increasing returns to group size means that regulators should be using larger inspection groups more often. Creating larger inspection groups comes at a cost: either new inspectors have to be hired or fewer inspections can be conducted. However, this trade-off is worthwhile if a regulator prefers more severe penalties, in which case it is optimal to shift to fewer inspections with larger-inspection groups. For example, suppose no more inspectors can be hired and the opportunity cost of adding an inspector to a team is foregoing a one-person inspection. The foregone inspection has a probability of receiving a facility shut-in of 0.021, however this probability is twelve times larger for the inspection that proceeds with an additional inspector.[34] If more severe sanctions have spillover effects to other nearby facilities (as in the case of Shimshack and Ward, 2005), then by increasing inspector group size, the overall impacts would be intensified. It is easier to make the policy recommendation to increase inspector group size when the cost of an additional inspector is low. In the case of offshore oil and gas facilities, the helicopter cost of transporting an inspector via helicopter is roughly the salary of the inspector.[35] Thus, if benefits of increasing the probability of imposing a facility shut-in by 0.252 exceeds the daily

[34] The average one-person inspection leads to 0.021 facility shut-ins (i.e., .015*1.38 from Table II), but adding one inspector to the average inspection increases the probability of a facility shut-in by 0.252 (Table IV).

[35] This is calculated as follows. Cost information on helicopters is found in the Congressional Budget Justification for FY2004 which described the closure of the Corpus Christi office. Annual variable costs for one helicopter were $150,000. In 2003, there were a total of 16 helicopters in the Gulf and 81 inspectors, which translates to five inspectors per helicopter trip on average. This means that helicopter costs, per inspector, per year were $30,000. The starting salary for an offshore inspector in 2003 was $31,830-$50,617 (http://www.rigzone.com/jobs/postings/3106/Engineers_and_Inspectors.asp). We only know how the cost of salaries has appreciated, not helicopters; in 2014 starting salaries ranged from 38, 790*to*84,139 (https://www.usajobs.gov/GetJob/PrintPreview/362456900).

cost of an inspector, shifting to more inspectors seems appropriate.

While we conclude that larger inspection groups issue more sanctions, it is important to know how this translates into safety outcomes. Our regressions examining self-reported incidents have low power but weakly point to improved safety outcomes (all coefficients are large, but statistically insignificant). It is possible that the sanctions available to inspectors are not stringent enough to reduce the risk of more accidents. Indeed this is a conclusion made after the BP Deepwater Horizon by the director of the offshore regulatory agency, who stated that "sanctions that are currently available to deter and punish violations of safety and environmental standards and regulations, must be substantially strengthened" (Bromwich, 2010). Since then, the three INCs discussed in this paper are still used; the average inspection in the Gulf has received more INCs, however civil penalties have not increased in frequency or magnitude.[36] Attempts to raise the penalties have not been authorized by Congress. It is also possible that the number of self-reported incidents is not accurately portraying the number of actual incidents. Government enforcement agencies often rely upon self-reports of incidents they would not otherwise detect. Thus, the more stringent enforcement brought about by increasing the number of inspectors might induce both deterrence and increased self-reporting. This is plausible since failure to report an incident is itself a violation, and enhanced scrutiny by inspectors might cause firms to both take better care to comply with the law and to self-report incidents if they happen. However, given the large size of our coefficients and the infrequency of spills, injuries, and fatalities, it is likely that there is a deterrent effect but we don't have the statistical power to precisely estimate it. As illustrated by the BP Deepwater Horizon spill, inattention to safety can have catastrophic consequences, and therefore a deeper examination of the deterrent effect of these sanctions is ripe for further research.

[36]According to a report analyzing enforcement actions before and after the BP oil spill, prepared by staff members of the House Natural Resources Committee " Dangerous Drillers: Offshore Safety Lapses Continue Three Years After BP Spill," http://democrats.naturalresources.house.gov/sites/democrats.naturalresources.house.gov/files/2013-05-10_BP_Spill_DangerousDrillers.pdf

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APPENDIX A: 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.[37]

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 when the interpretation of the definition of a specific component or the timing of the incident might influence the enforcement action taken.

[37] For the full list of PINCs, see:
http://bsee.gov/uploadedFiles/BSEE/Enforcement/Inspection_Programs/OFFICEPINCLIST_JBA%20Changes%20Included.pdf

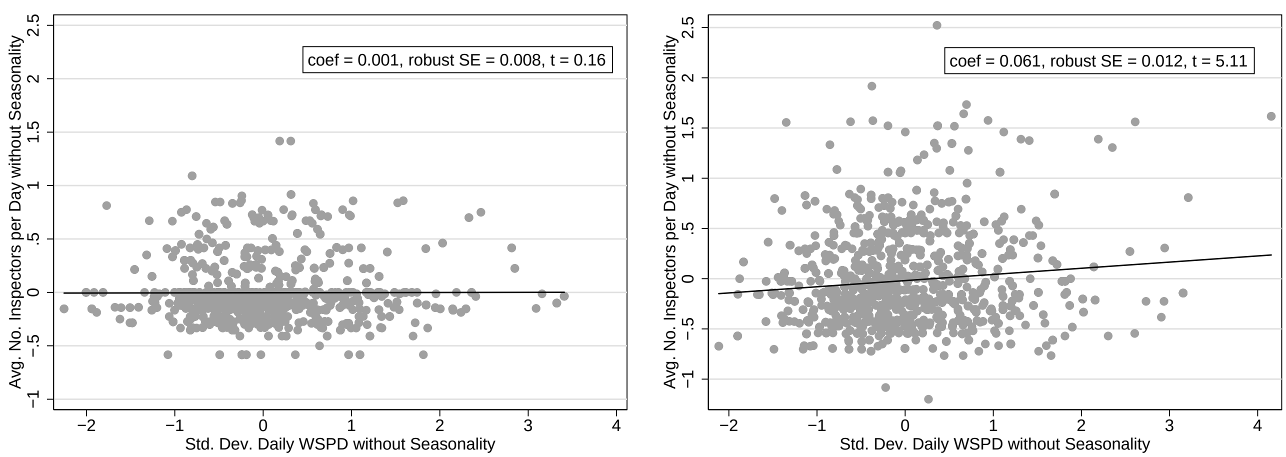
APPENDIX B: GRAPHICAL ILLUSTRATION OF FIRST STAGE REGRESSION

Figure 3 illustrates the first stage of our instrumental variable estimation strategy. The deseasonalized observations are obtained by regressing standard deviation of daily wind speed on year-months fixed effects and then predicting the residual standard deviation of wind speed. We do the same for daily average inspector group size).

Consistent with Figure 2, Panel A shows no relationship between standard deviation of wind speed and inspector group size prior to the closure of the Corpus Christi airport. Panel B reveals the predictive power of the standard deviation in wind speed as an instrument for inspector group size after the closure of the Corpus Christi airport. A 1 unit increase in standard deviation in wind speed corresponds to a 0.062 increase in inspector group size.

Figure 3: 2SLS First Stage Regression

(a) First Stage Regression, Before Airport Closure (b) First Stage Regression, After Airport Closure



Notes: Observations are residuals from regressions of the daily average number of inspectors (y-axis) or daily standard deviation of wind speed (x-axis) on year-months fixed effects.

APPENDIX C: COMPARISON OF OLS ESTIMATES IN LAKE JACKSON VS ALL DISTRICTS

The main results shown in Table IV of the paper use data on platform inspections in the Lake Jackson district. In this appendix, we explore whether our results are similar if we use data on all platform inspections in the Gulf of Mexico. Table IX shows OLS estimates of the impact of inspector group size on enforcement actions in Lake Jackson versus all districts in the Gulf of Mexico. Overall the estimates are quantitatively quite similar, suggesting that Lake Jackson is representative of all districts in the Gulf of Mexico.

Similarly, Table X shows OLS estimates of the impact of inspector group size on incidents and fatalities and injuries using data from Lake Jackson versus data from all districts in the Gulf of Mexico. The point

TABLE IX

Comparison of OLS Estimates on Enforcement Actions for Lake Jackson vs All Districts

	Warnings		Component		Facility		Weighted	
	Lake Jackson (1)	All Districts (2)	Lake Jackson (3)	All Districts (4)	Lake Jackson (5)	All Districts (6)	Lake Jackson (7)	All Districts (8)
No. Inspectors	.049	.126***	.211***	.158***	.034**	.010***	.606***	.480***
	(.052)	(.021)	(.052)	(.022)	(.014)	(.003)	(.150)	(.071)
Year-Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Operator Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	2,008	20,545	2,008	20,545	2,008	20,545	2,008	20,545
R^2	.193	.118	.215	.116	.108	.028	.219	.142
Mean of Dep. Var.	.455	.309	.483	.288	.034	.020	1.556	.963

Notes: Sample for "Lake Jackson" estimates includes production inspections in Lake Jackson between October 2003 and September 2010. Sample for "All Districts" estimates includes production inspections in all districts 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). Robust standard errors are clustered by operator (for 77 operators in "Lake Jackson" sample and 132 operates in "All Districts" sample). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

estimates are similar in both samples, but the sample size is much larger in the case of all districts and therefore the standard errors are much lower.

TABLE X

Comparison of OLS Estimates on Incidents and Injuries and Fatalities for Lake Jackson vs All Districts

	6 Mo. After		12 Mo. After		6 Mo. After		12 Mo. After	
	Lake Jackson (1)	All Districts (2)	Lake Jackson (3)	All Districts (4)	Lake Jackson (5)	All Districts (6)	Lake Jackson (7)	All Districts (8)
No. Inspectors	.006	.008**	.001	.016***	.000	.001	-.003	.001
	(.012)	(.004)	(.021)	(.004)	(.005)	(.001)	(.007)	(.001)
Year-Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Operator Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
n	2,008	20,545	2,008	20,545	2,008	20,545	2,008	20,545
R^2	.172	.171	.242	.229	.232	.022	.322	.028
Mean of Dep. Var.	.055	.077	.109	.143	.006	.003	.011	.006

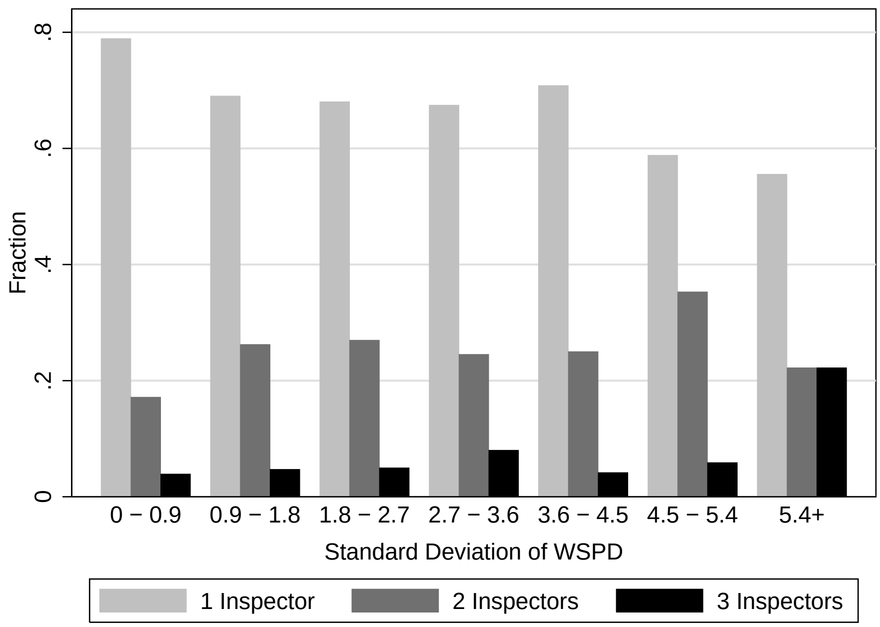
Notes: Sample for "Lake Jackson" estimates includes production inspections in Lake Jackson between October 2003 and September 2010. Sample for "All Districts" includes production inspections in all districts between October 2003 and September 2010. Dependent variables are the number of incidents and injuries & fatalities within 6 months and 12 months after a inspection. Robust standard errors are clustered by operator (for 77 operators in "Lake Jackson" sample and 132 operators in "All Districts" sample). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

APPENDIX D: WHY ARE THE IV ESTIMATES LARGER THAN THE OLS ESTIMATES?

As Table IV in the paper illustrates, the IV estimates of the impact of inspector group size on enforcement actions are always larger than the corresponding OLS estimates. 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. As discussed in section 5.2, measurement error in the number of inspectors is not as likely as non-linearity in the effects, and therefore we examine this in more detail. 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.

Figure 4 plots the relationship between standard deviation of daily wind speed (in 0.9 m/s bins) and the fraction of 1-inspector, 2-inspector, and 3+-inspector cases. Consistent with Figure 2, we find that the fraction of 1-inspector cases is decreasing with standard deviation in wind speed, while the fraction of inspections with 2 inspectors tends to increase, except for the highest bin. The fraction of 3+-inspector cases is relatively constant for low to modest levels of standard deviation in wind speed, but exhibits a sharp increase at the highest level, implying that the instrument particularly affects the shift in moving from 2 to 3+ inspectors.

Figure 4: Share of Inspections with One, Two, and Three Inspectors by Standard Deviation of Wind Speed



This observation is confirmed in Table XI which reports OLS and IV weights when moving from one to two and from two to three inspectors. These weights are calculated using the method by Lochner and Moretti (2015) and they reflect how much of the average increase in inspector group size in the OLS and IV approach, respectively, is due to a particular level increase in group size. The IV weight when moving from two (one) to three (two) inspectors is larger (smaller) than the corresponding OLS weight.

Following Lochner and Moretti (2015) we re-weight the OLS estimates in Table V using the estimated IV weights from Table XI, and use a general Wald test, robust to a non-linear relationship between the endogenous regressors and the dependent variable, to test for exogeneity.[38] As Table XII illustrates, the

[38]If the true relationship between the number of inspectors and enforcement is non-linear, then the tradi-

TABLE XI

Comparison of OLS and IV Weights

	One to Two	Two to Three+
OLS weights	0.736	0.264
IV weights	0.653	0.347

Notes: Weights placed moving from one inspector to two inspectors and from two inspectors to three or more inspectors. Weights are calculated using the method by Lochner and Moretti (2015).

re-weighted OLS coefficients are larger than the OLS estimates, 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 exogeneity. 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.

TABLE XII

Re-weighted OLS Coefficients

	Warnings		Component		Facility		Weighted	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	ROLS	OLS	ROLS	OLS	ROLS	OLS	ROLS
No. Inspectors	.049	.080	.211***	.261***	.034**	.046**	.606***	.791***
	(.052)	(.058)	(.052)	(.085)	(.014)	(.019)	(.150)	(.245)
General Wald (p-value)		.850		.698		.048		.380

Notes: OLS estimates are the same as found in Table IV. Re-weighted OLS estimates from derived by using IV weights to calculate an average of the coefficients in Table V. The General Wald test (Lochner and Moretti, 2015) compares the re-weighted OLS in this table to the linear IV estimator (found Table IV).

APPENDIX E: ADDITIONAL TABLES

Table XIII shows OLS and IV estimates on the impact of an additional inspector on the probability of an enforcement action. The OLS estimates indicate that an additional inspector leads to a significant increase in the probability of a component shut-in, a facility shut-ins, and a weighted combination of enforcement actions. Similar to the findings of the main paper, only the most stringent enforcement actions, facility shut-ins, are statistically significantly more likely to occur with more inspectors. The point estimate indicates that adding an inspector increases the probability of a facility shut-ins by 21.3 percentage points.

Table XIV shows OLS and IV estimates on the impact of an additional inspector on the probability of an incident and an injury and fatality. The regressions are somewhat inconclusive, because of low power, but the IV estimates weakly point to better safety outcomes.

Tables XV and XVI report OLS and IV estimates on the impact of inspector group size on enforcement and deterrence for all covariates included in equation 1.

tional Hausman test is uninformative.

TABLE XIII

Impact of the Number of Inspectors on the Probability of an Enforcement Action

	Warnings		Component		Facility		Weighted	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
No. Inspectors	.017	.116	.077***	.042	.033***	.213**	.080***	.087
	(.021)	(.247)	(.014)	(.209)	(.012)	(.100)	(.019)	(.284)
Year-Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Operator Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	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
R^2	.203	.189	.201	.199	.114	-.233	.212	.212
First Stage F-stat.		14.44		14.44		14.44		14.44
Mean of Dep. Var.	.3	.3	.2	.2	.0	.0	.4	.4

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 77 operators). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

TABLE XIV

Impact of the Number of Inspectors on the Probability of an Incident and a Fatality and Injury

	6 Mo. After		12 Mo. After		6 Mo. After		12 Mo. After	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
No. Inspectors	.009	-.121	.001	-.138	-.001	-.044	-.001	-.025
	(.011)	(.096)	(.013)	(.106)	(.004)	(.040)	(.006)	(.033)
Year-Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Operator Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	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
R^2	.159	.057	.209	.140	.110	-.007	.159	.137
First Stage F-stat.		14.44		14.44		14.44		14.44
Mean of Dep. Var.	.0	.0	.1	.1	.0	.0	.0	.0

Notes: Sample includes production inspections in Lake Jackson between October 2003 and September 2010. Dependent variables are the number of incidents and injuries & fatalities within 6 months and 12 months after a inspection. In the case of the IV estimates, *No. Inspectors* is instrumented for using weather. Robust standard errors are clustered by operator (for 77 operators). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

TABLE XV

Impact of the Number of Inspectors on Enforcement Actions

	Warnings		Component		Facility		Weighted	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)	OLS (7)	IV (8)
No. Inspectors	.049	.176	.211***	.516	.034**	.252**	.606***	2.216
	(.052)	(.740)	(.052)	(.620)	(.014)	(.118)	(.150)	(1.746)
Platform Age (years)	.006	.006	-.009	-.009	.001	.001	-.007	-.008
	(.007)	(.007)	(.008)	(.008)	(.001)	(.001)	(.022)	(.023)
Distance to Shore (miles)	.001	.002	.002**	.003*	.000	.001**	.007**	.010**
	(.001)	(.001)	(.001)	(.002)	(.000)	(.000)	(.003)	(.004)
Water Depth (1,000 feet)	.147	.132	-.029	-.065	-.022*	-.048**	-.001	-.190
	(.092)	(.097)	(.263)	(.268)	(.013)	(.021)	(.615)	(.640)
Inactive (Indicator)	-.146**	-.142**	-.273***	-.263***	-.009	-.002	-.727***	-.676***
	(.058)	(.060)	(.061)	(.057)	(.013)	(.015)	(.189)	(.187)
Production (mmBOE in month prior)	-.586***	-.620*	-.325	-.407	-.007	-.065	-1.262	-1.696
	(.212)	(.340)	(.516)	(.526)	(.040)	(.056)	(1.192)	(1.333)
Major Complex (Indicator)	.085	.080	.113*	.102*	.023*	.015	.401**	.344**
	(.067)	(.056)	(.060)	(.061)	(.013)	(.014)	(.168)	(.159)
Manned 24 hrs (Indicator)	.045	.039	.202	.188	-.011	-.021	.408	.330
	(.096)	(.098)	(.179)	(.175)	(.017)	(.019)	(.473)	(.444)
Number of Wells (t)	-.011**	-.012**	.011	.010	.004***	.003***	.025	.020
	(.005)	(.006)	(.008)	(.009)	(.001)	(.001)	(.019)	(.020)
Corpus Christi (Indicator)	-.108	-.095	-.144	-.112	.037	.060*	-.249	-.079
	(.104)	(.142)	(.185)	(.204)	(.028)	(.033)	(.436)	(.485)
New Inspector (Indicator)	-.049	-.148	-.006	-.246	-.007	-.180*	-.090	-1.358
	(.132)	(.578)	(.296)	(.550)	(.031)	(.098)	(.688)	(1.593)
Cum. Inspections by I (last 5 yrs)	-.000	-.000	.000*	.001	-.000	.000	.000	.001
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.001)	(.001)
No. of Lessees (t)	-.002	-.003	.016	.015	-.002	-.003	.023	.017
	(.018)	(.018)	(.023)	(.021)	(.004)	(.004)	(.064)	(.055)
Working Interest of O (%) (t)	.001	.001	.001	.001	.000	.000	.005	.004
	(.001)	(.001)	(.001)	(.001)	(.000)	(.000)	(.003)	(.003)
No. of P Operated by O (t)	.002*	.002*	-.002	-.002	-.000	-.000	-.002	-.002
	(.001)	(.001)	(.002)	(.001)	(.000)	(.000)	(.004)	(.004)
Post Hurricane (Indicator)	-.663**	-.670**	-.186	-.202	-.000	-.012	-1.036	-1.122
	(.314)	(.315)	(.427)	(.429)	(.039)	(.073)	(.995)	(1.131)
Cum. Inspections of P by I, past 5 yrs	-.067**	-.061*	-.108***	-.095*	-.005	.005	-.304***	-.232*
	(.028)	(.033)	(.039)	(.051)	(.010)	(.010)	(.103)	(.129)
Cum. Inspections of P (t-1)	.008	.008	.023*	.022*	-.001	-.002	.050	.046
	(.007)	(.007)	(.012)	(.012)	(.001)	(.001)	(.031)	(.031)
Constant	1.133***	1.093***	-.597	-.695	-.138	-.208**	-.614	-1.131
	(.360)	(.380)	(.764)	(.726)	(.084)	(.105)	(2.004)	(1.895)
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
R^2	.193	.189	.215	.202	.108	-.115	.219	.164
Mean of Dep. Var.	.455	.455	.483	.483	.034	.034	1.556	1.556

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 77 operators). *** Statistically significant at the 1% level; ** 5% level; * 10% level.

TABLE XVI

Impact of the Number of Inspectors on Incidents and Fatalities and Injuries

	6 Mo. After		12 Mo. After		6 Mo. After		12 Mo. After	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)	OLS (7)	IV (8)
No. Inspectors	.006	-.147	.001	-.120	.000	-.086	-.003	-.012
	(.012)	(.120)	(.021)	(.197)	(.005)	(.089)	(.007)	(.053)
Platform Age (years)	-.001	-.001	-.001	-.001	.000	.000	.000	.000
	(.002)	(.002)	(.002)	(.002)	(.000)	(.000)	(.001)	(.001)
Distance to Shore (miles)	.000	-.000	.000	-.000	.000*	-.000	.000*	.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Water Depth (1,000 feet)	.179***	.197***	.291***	.305***	-.010	.001	-.053**	-.052*
	(.038)	(.027)	(.037)	(.040)	(.009)	(.009)	(.025)	(.028)
Inactive (Indicator)	-.012	-.017*	-.028*	-.032**	.006*	.004	.013*	.012*
	(.011)	(.010)	(.016)	(.015)	(.004)	(.004)	(.007)	(.007)
Production (mmBOE in month prior)	-.203**	-.162	-.359***	-.327***	.310*	.334*	.631*	.633**
	(.094)	(.104)	(.115)	(.122)	(.166)	(.181)	(.341)	(.320)
Major Complex (Indicator)	-.002	.003	.001	.006	-.005**	-.002	-.005	-.004
	(.009)	(.012)	(.013)	(.015)	(.002)	(.004)	(.003)	(.004)
Manned 24 hrs (Indicator)	.056***	.064***	.080**	.086***	-.008	-.004	-.025*	-.025*
	(.016)	(.019)	(.032)	(.033)	(.008)	(.007)	(.014)	(.015)
Number of Wells (t)	.000	.001	.002	.002	.001	.001	.002	.002
	(.003)	(.003)	(.005)	(.005)	(.001)	(.001)	(.001)	(.001)
Corpus Christi (Indicator)	.000	-.016	-.013	-.025	.011*	.002	.009	.008
	(.020)	(.024)	(.029)	(.037)	(.006)	(.010)	(.010)	(.010)
New Inspector (Indicator)	-.031	.089	-.084	.011	-.001	.067	-.007	.001
	(.039)	(.086)	(.071)	(.180)	(.008)	(.075)	(.013)	(.035)
Cum. Inspections by I (last 5 yrs)	.000	-.000	-.000	-.000	.000	-.000	.000	-.000
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
No. of Lessees (t)	.009***	.009***	.004	.005	.004**	.004**	.004**	.004**
	(.003)	(.003)	(.004)	(.004)	(.002)	(.002)	(.002)	(.002)
Working Interest of O (%) (t)	.000**	.000***	.001	.001*	.000*	.000**	.000*	.000*
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
No. of P Operated by O (t)	-.000	-.001	-.001*	-.001**	.000	.000	.000	.000
	(.000)	(.000)	(.001)	(.001)	(.000)	(.000)	(.000)	(.000)
Post Hurricane (Indicator)	.160	.168	.202	.208	.016	.021	.021	.022
	(.161)	(.182)	(.150)	(.163)	(.011)	(.026)	(.019)	(.020)
Cum. Inspections of P by I, past 5 yrs	-.002	-.009	.000	-.005	.002	-.002	-.002	-.002
	(.008)	(.011)	(.011)	(.012)	(.004)	(.005)	(.003)	(.003)
Cum. Inspections of P (t-1)	.002	.003	.004*	.004**	.000	.000	.001	.001
	(.002)	(.002)	(.002)	(.002)	(.000)	(.000)	(.001)	(.001)
Constant	-.163***	-.114	-.353***	-.315***	-.075***	-.048	-.102**	-.099**
	(.047)	(.072)	(.113)	(.113)	(.026)	(.034)	(.039)	(.049)
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
R^2	.172	.086	.242	.219	.232	.067	.322	.321
Mean of Dep. Var.	.055	.055	.109	.109	.006	.006	.011	.011

Notes: Sample includes production inspections in Lake Jackson between October 2003 and September 2010. Dependent variables are the number of incidents and injuries & fatalities within 6 monhts and 12 months after a inspection. In the case of the IV estimates, *No. Inspectors* is instrumented for using weather. Robust standard errors are clustered by operator (for 77 operators). *** Statistically significant at the 1% level; ** 5% level; * 10% level.