How Predictable are Environmental Compliance Inspections?

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In the U.S. many major environmental regulations are enforced using a deterrence-framework: that is, regulations are enforced through unannounced compliance inspections and fines for any violations discovered during the course of those inspections. According to Gray and Shimshack (2011), most policy-makers and scholars generally believe that effective pollution regulations require an enforcement regime that includes recurrent inspections and sanctions, and survey evidence suggests that a traditional regulatory structure with rigorous monitoring and enforcement is a primary motivator of facilities' environmental compliance decisions.

Numerous empirical studies covering a wide range of environmental regulations and regulated populations provide evidence that deterrence-based enforcement does increase compliance rates. For example, Gray and Deily (1996) and Gray and Shadbegian (2005) examine air pollution compliance for steel mills and pulp and paper mills in the U.S., respectively, and find that both inspections and enforcement actions have a statistically significant positive impact on compliance. Looking at compliance with U.S. water regulations, Earnhart (2004) and Glicksman and Earnhart (2007) similarly find that inspections and sanctions deter violations at water treatment plants and chemical facilities, respectively. Stafford (2002) shows that compliance inspections and penalties for violations have a significant deterrent effect on violations at facilities subject to hazardous waste regulations.[1]

Most empirical analyses of enforcement and compliance generally estimate the likelihood of an inspection or the number of inspections for a given time period, with the particular time period selected based on data availability. While the probability of inspection may depend on the characteristics of a facility – including its past compliance history – it is almost never modeled as depending on the length of time since the last

[1] See Gray and Shimshack (2011) for a comprehensive survey of the empirical literature on environmental monitoring and enforcement.

inspection. This is not that surprising given that most of the theoretical models on which the empirical studies are based assume that the likelihood of an inspection at a particular facility is fixed for a particular time period. In fact, many theoretical models are static and thus time does not enter into the design of optimal enforcement at all. Where time is expressly modeled, time periods are usually discrete and, to my knowledge, time since the last inspection has not been a factor in the design of an optimal enforcement regime. While these choices make it easier to model environmental compliance behavior and to develop optimal enforcement regimes, it is not clear how accurate such assumptions are. It is reasonable to think that the probability that a facility is inspected may depend on how long it has been since the last inspection, particularly if a regulatory agency's charge is to inspect each facility at least once every two years.

The purpose of this paper is to provide additional insight into the timing of environmental compliance inspections to help scholars and policy makers better understand the effectiveness of such inspections in increasing compliance. In particular, this paper focuses on modeling the timing of compliance inspections conducted at hazardous waste generators that are regulated under the Resource Conservation and Recovery Act. Once we have a better understanding of the actual timing of compliance inspections we can then examine the extent to which regulated entities perceive the underlying process for inspections and how their compliance decisions depend on that perception.

The remainder of the paper is organized as follows: Section 1 provides a theoretical framework for the empirical analysis and discusses the related literature. Section 2 discusses the institutional setting for the analysis, namely the inspection regime for the EPA's hazardous waste program. Section 3 presents the econometric methodology while Section 4 describes the data used in the analysis. Section 5 presents the results of the duration models and Section 6 compares the duration results to other more common models of inspections. Finally, Section 7 concludes with a discussion of the next steps in this research project.

1. Theoretical Framework and Related Literature

Becker's (1968) paper on the economics of crime provides the basic framework for the deterrence-based approach to regulatory violations. Becker assumes potential criminals are rational and will commit a crime whenever the expected value of the crime is greater than the expected cost of the crime. To deter criminals, one must increase the expected cost of the crime either by increasing the likelihood that the crime is detected or the punishment associated with the crime. Becker's model spawned a large literature on the economics of crime and regulatory enforcement that starts with the same basic assumption that potential criminals or violators make decisions based on a rational comparison of costs.[2]

Russell, Harrington, and Vaughn (1986) were one of the first to take the general models on the economics of crime and explicitly apply them to environmental regulation. Since that time many additional models of environmental compliance and enforcement have been built on this "rational polluter" framework extending the basic model by allowing for complexities such as imperfect information, self-reporting, and principal-agent relationships, to name a few. While the majority of these extensions assume a static setting, there are several papers that have presented dynamic models on enforcement and compliance.[3] One of the most influential of these models is Harrington's (1988) targeted enforcement model which uses changes in future inspection activity to motivate current compliance and shows that such a regime can maintain a higher level of compliance than can be obtained through more traditional, non-targeted enforcement. Harrington's model has been extended theoretically by a number of papers (see, for example, Harford and Harrington (1991), Raymond (1999), Friesen (2003)) and has also been the focus of a number of empirical studies (see for example, Helland (1998) and Stafford (2007)).

As discussed in the introduction, while both the theoretical targeting models and the empirical tests of such models have explicitly examined the relationship between past and future compliance and enforcement, the models and estimates have used a series of discrete time periods such as months or years rather than looking at inspections across time. For example, most empirical studies of enforcement estimate the likelihood of an

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[2] See Polinsky and Shavell (2000) for an overview of this literature.
[3] See Cohen (1999) and Heyes (2000) for surveys of this literature.

inspection for a given time period (or in some cases the number of inspections for a given time period) choosing the time period for the analysis based on the type of data available. To my knowledge, there is only one study other than this one that focuses explicitly on inspection timing. Rousseau (2007) incorporates a duration model into her examination of inspections of textile plants in Flanders.[4] In particular, she uses a Cox partial likelihood model to estimate the length of time between environmental inspections for regulated entities based on the entities' characteristics and past compliance statuses. She finds that the Flemish environmental inspection agency does use targeting, particularly targeting based on past compliance behavior and the entities' overall capacity, to select the entities that it inspects. Since the focus of the paper is to examine the extent of targeting, Rousseau does not analyze whether a duration model provides a better fit to the data than a standard model.

This paper differs from that of Rousseau in two primary ways. First, and most obvious, is that this paper looks at U.S. hazardous waste inspections across a wide range of industries as opposed to Flemish environmental inspections at textile plants across a variety of media (e.g., water pollution, air pollution, toxic substances). Second, this paper uses multiple different duration analyses in order to assess how well different models predict inspections – the focus is on how well the models predict inspections, not using the model to test a particular enforcement theory.

2. Institutional Setting

Because environmental regulation in the U.S. is the result of a series of different pieces of legislation, there are separate media programs that regulate air pollution, water pollution, and hazardous waste. Each program tracks the individual facilities that it regulates separately and has its own enforcement regime. An inspection conducted by the air program focuses on determining compliance with air regulations, not water or hazardous waste regulations.[5] Thus, in examining the timing of environmental inspections

[4] Nadeau (1997) estimates a duration model of plant <u>non-compliance</u> in the U.S., but chooses to model <u>inspections</u> as a Poisson process.
[5] Programs can co-operate and conduct multi-media inspections, but the majority of inspections are single program inspections.

it makes sense to focus on one particular media program. This paper focuses on the hazardous waste program because regulatory inspections are the primary way in which hazardous regulations are enforced. Perhaps most importantly, hazardous waste facilities are not required to self-report compliance status as facilities regulated subject to Clean Air Act and Clean Water Act regulations must do.

Hazardous waste is regulated under the Resource Conservation and Recovery Act (RCRA). RCRA Subtitle C, Section §3007 gives EPA the authority to conduct compliance and evaluation inspections of hazardous waste facilities for the purpose of developing regulations, preparing permits, or ensuring compliance with RCRA regulations. Regulated entities must grant authorized officials access to all records at hazardous waste management facilities at all reasonable times and must allow officials to obtain samples of any wastes present and determine compliance with all applicable requirements of RCRA.[6]

There are a number of different types of inspections. Some inspections are not focused on enforcement such as inspections designed to collect information to help EPA develop new rulemakings or compliance assistance inspections conducted at the request of the regulated entity. While these types of inspections will be scheduled in conjunction with the facility, EPA's policy is that compliance inspections are unannounced. The primary types of compliance inspections include:

- Compliance Evaluation Inspections — Routine inspections to evaluate compliance with RCRA. These inspections usually encompass a file review prior to the site visit; an on-site examination of generation, treatment, storage, or disposal areas; a review of records; and an evaluation of the facility's compliance with RCRA.
- Comprehensive Ground Water Monitoring Evaluations — Inspections to ensure that ground water monitoring systems are designed and functioning properly at RCRA land disposal facilities.

[6] Under the U.S. Supreme Court decision in Marshall v. Barlow (436 U.S. 307, 322-24 (1978)), business owners and operators have an expectation of privacy against unreasonable administrative searches of their commercial property and warrantless searches cannot generally be conducted. However, there is an exception for "pervasively regulated businesses" subject to "longstanding governmental regulation." Additionally, probable cause for obtaining a warrant can be established by showing that the entity is being inspected according to a neutral inspection regime. In practice, few entities challenge EPA inspections without warrants (Steinway, 2009).

- Compliance Sampling Inspections — Inspections to collect samples for laboratory analysis. A sampling inspection may be conducted in conjunction with other inspections.
- Operations and Maintenance Inspections — Inspections to ensure that ground water monitoring and other systems at closed land disposal facilities continue to function properly.
- Laboratory Audits — Inspections of laboratories performing monitoring analyses to ensure that these laboratories are using proper sample handling and analysis protocols.

While federal EPA employees from headquarters or one of EPA's ten regional offices may conduct compliance inspections, most inspections are conducted by state and local agencies.[7]

RCRA's Compliance Monitoring Strategy requires that all facilities that are permitted to treat, store, or dispose hazardous wastes (facilities known as TSDFs) be inspected at least once every two years and that 20 percent of large quantity generators (LQGs) be inspected each year. Additionally, the Hazardous and Solid Waste Amendments (HSWA) to RCRA require that all federal- and state-operated facilities be inspected annually. Other sites may be inspected less frequently. When a violation is detected, regulators can choose from a variety of enforcement actions including administrative orders, civil lawsuits, or criminal lawsuits, depending on the nature and severity of the problem and may conduct additional case development inspections to gather data to support a particular enforcement action.

According to EPA's RCRAInfo database, in 2010 federal and state regulators conducted 32,240 inspections at 24,995 regulated hazardous waste facilities.[8] While it is difficult to determine exactly the number of facilities regulated under RCRA in 2010, the

[7] Under Section §3006 of RCRA, EPA may authorize qualified states to administer and enforce their own hazardous waste program. States with final authorization administer their hazardous waste programs in lieu of EPA's federal program. However, even in states with final authorization, EPA retains the authority to conduct independent inspections and can enforce any provision of an authorized state's approved program, including state requirements that are more stringent than the federal requirements.

[8] RCRAInfo is EPA's primary database for all facilities regulated under RCRA. It contains data on all inspections and enforcement actions conducted under RCRA's authority.

total number most likely exceeds 600,000.[9] Thus less than 1 in 20 regulated facilities was inspected in 2010. Of those facilities that were inspected, the average number of inspections was 1.3 per facility although almost 84 percent (21,103 facilities) were inspected only once that year. Just under 11 percent (2,724 facilities) were inspected on two separate dates while the remaining 6,217 inspections took place at approximately 5 percent (1,168) of inspected facilities. Figures 1 and 2 show the breakdown of 2010 inspections by primary inspection type and the type of inspector, respectively.[10] Note that almost 60 percent of inspections are general compliance evaluation inspections and that over 90 percent of inspections are conducted by state regulators.

Over the five year period of 2006-2010, 150,756 inspections were conducted, or roughly 30,000 per year. Over this period of time 80,798 unique facilities were inspected, less than one fifth of the regulated universe. Almost 70 percent (55,800 facilities) received only one inspection over this time period, while about six percent (4,507) received five or more inspections. Thus there are significant differences in the likelihood of inspections across regulated facilities. One goal of this paper is to better understand the factors that affect the likelihood of an inspection at any particular facility as well as the extent to which the timing of such inspections can be and is predicted by regulated entities.

3. Econometric Methodology

As discussed in Section 1, most empirical analyses of environmental enforcement focus on estimating the probability of a facility being inspected during a particular time period or the number of inspections that occur during a fixed time period. The focus of this analysis is length of time between inspections and the likelihood that a facility that has not

[9] RCRAInfo contains records for over 760,000 facilities that have been subject to RCRA regulations over time, although not all of those facilities were active in 2010.
[10] Over 95 percent of inspections list only one type of inspection and one inspection agency. For the remaining records, I created an inspection type hierarchy and an inspection agency hierarchy and assigned both a primary inspection type and a primary inspector type based on those hierarchies. This process is explained in more detail in Appendix A.

been inspected for a given number of days will be inspected the following day.[11] To conduct the analysis I use a variety of survival or duration models.

In general survival models examine how various explanatory variables affect the "survival" time of subjects in the analysis.[12] Since the focus of the analysis is on the length of the particular "spell" in question – in this case, the length of time between inspections – the particular dates on which subjects begin a spell do not have to be the same across subjects. To conduct a survival analysis one must first identify the universe that one wants to examine and then observe the times at which various spells occur. Once one has developed a dataset with the times at which subjects enter and exit a spell, one can conduct a variety of different analyses to analyze the duration of spells and the ways in which various factors influence the duration. Alternatively one can focus not on the length of spells but rather on the probability of exiting a spell conditional on having survived up to a particular interval which is known as the hazard rate or hazard function.

Survival models all share the same basic setup. Let T be a non-negative random variable representing the spell duration for a particular subject. Then T has an associated density function $f(t)$ and a cumulative distribution function $F(t)$ where t is a realization of T. The probability that the spell length is t or longer is given by the survivor function:

$$S(t) = 1-F(t) = \Pr(T>t).$$

And the probability that one who has survived up to t exits a spell at t is:

$$\lambda(t) = \frac{f(t)}{S(t)},$$

also known as the hazard function. If $\lambda(t)$ is increasing in t, the spell exhibits positive duration dependence. That is, the longer the spell, the higher the probability that one will

[11] I chose to focus on days as the unit of measure. One could conduct the same analysis using any discrete measure of time.
[12] See Wooldridge (2010), Chapter 22 "Duration Models" for a more comprehensive discussion of the use of survival models.

exit from the spell. We would likely see positive duration dependence if facilities had to be inspected with a particular frequency, e.g. once every two years. The longer the time since the last inspection, the higher the probability of inspection will be. Alternatively, we might see negative duration dependence if the agency engaged in inspection targeting where some facilities were inspected with a high frequency and some inspected with a low frequency. Finally, spells may not exhibit duration dependence if the probability of inspection is constant across time.[13]

We can write *t*, the length of a particular spell, as a function of a vector of explanatory variables *x* and an error term ε:

$$t_j = \beta_0 + x_j \beta_x + \varepsilon_j$$

Then the hazard function can be written as:

$$\lambda_j(t) = g\left(t, \beta_0 + x_j \beta_x\right).$$

where the function *g(·)* depends on the distributional assumptions one makes about ε_j. Similarly, the survivor function can be expressed as

$$S_j(t) = h\left(t, \beta_0 + x_j \beta_x\right).$$

The Kaplan-Meier estimator is a nonparametric estimator of the survivor function at time *t* given by:

$$\hat{S}(t) = \prod_{j \mid t_j \leq t} \left(\frac{n_j - d_j}{n_j} \right).$$

[13] A constant hazard rate generates a Poisson count distribution.

where n_j is the number of subjects "at risk" at time t_j and d_j is the number of exits at time t_j.[14] A nonparametric estimate of the hazard function can also be derived using a related process.[15] Neither of these estimates makes any adjustments for recurrent events (i.e., multiple inspections at the same facility), as there are no explanatory variables in the model. However, one can estimate the survivor and hazard functions separately for subsets of the universe and test whether the hazard functions are statistically significant.

If one wants to include explanatory variables in the analysis there are two general approaches that can be used, semiparametric and parameteric. The most common semiparametric model is the Cox proportional hazards model which assumes that the hazard rate for an individual subject *j* can be expressed as:

$$\lambda\left(t \mid x_j\right) = \lambda_0(t)e^{x_j\beta_x}$$

where $\lambda_0(t)$ is a baseline hazard function common to all subjects. The model is then estimated using a partial likelihood estimator that does not require that the baseline hazard be estimated.[16] The explanatory variables in this model shift the hazard function multiplicatively and the ratio of any two subjects' hazard rates at a given point in time is constant as long as the covariates do not change over time. One advantage of this model is that it allows one to incorporate explanatory variables into the model but does not require one to make assumptions about the baseline hazard model which, if wrong, could result in misleading results. The disadvantage is that there is a loss in efficiency and if one knew the functional form for the baseline hazard one could obtain better estimates of the coefficients. Additionally while one does not have to make assumptions about the baseline hazard, one must assume that all subjects have the same baseline hazard which could also result in misleading conclusions if the assumption is not correct. However, one can stratify the sample and allow for the baseline hazard to vary across the strata. In this case, the coefficients on the explanatory variables are not allowed to vary across strata. To control for multiple spells at individual facilities, the errors can be clustered by facility.

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[14] The variable t_j measures analysis time, not a specific date.
[15] I ran the analysis in Stata which uses the Nelson-Aalen estimator of the cumulative hazard function and smooths it using a kernel estimator to estimate the hazard function.
[16] Cox (1972) presents the partial likelihood estimator

By making an initial assumption about the distribution of the hazard function, parametric models can use the data on spells more efficiently than non- and semi-parametric models. The model is then estimated using maximum likelihood estimation. There are a number of commonly used parametric models. The Exponential model is the simplest one as it assumes that the baseline hazard rate is constant which implies that the underlying cumulative distribution function of the length of spells has an exponential distribution. If one believes that the hazard function is not constant, there are a number of alternative models that can be estimated. The Weibull model assumes that the length of spells has a Weibull distribution which results in a baseline hazard function that can be written as:

$$\lambda_0(t) = \gamma \alpha t^{\alpha-1}$$

where γ and α are non-negative parameters of the model that that will also be estimated. When α equals 1 the Weibull model reduces to the exponential model with a constant hazard rate equal to γ. If α is greater (less) than one, the hazard rate exhibits positive (negative) duration dependence. Note that in this model, the hazard rate is either monotonically increasing, monotonically decreasing or constant. The Gompertz model also allows for a monotonically increasing or decreasing hazard rate, but unlike the Weibull model, the baseline hazard changes exponentially with time:

$$\lambda_0(t) = \gamma e^{\alpha t}.$$

Note that this model reduces to the exponential model if α equals 0. The Log-Logistic model allows for a baseline hazard rate that can both increase and decrease. In this model, the baseline hazard rate is expressed as:

$$\lambda_0(t) = \frac{\gamma \alpha t^{\alpha-1}}{1 + \gamma t^{\alpha}}.$$

When γ is less than one, the hazard rate increases up to a certain point in time and then decreases. When γ is greater than or equal to one the hazard rate is monotonically decreasing. In all of these models, the explanatory variables serve to shift the hazard function. As with the Cox model, one can stratify the sample and allow for the baseline hazard to vary across the strata but the coefficients on the explanatory variables are not allowed to vary across strata. To control for multiple spells at individual facilities, errors are clustered by facility.

4. Description of the Data

Data on facilities subject to RCRA regulation comes from two primary sources, both of which are publicly available on EPA's website: the RCRAInfo database and the Biennial Reporting System (BRS). RCRAInfo contains information on all facilities that are or have been regulated under RCRA Subtitle C, i.e., facilities subject to RCRA hazardous waste regulations. The dataset contains information on facility characteristics, including facility status and regulated activities, and is updated periodically. The dataset also includes information on all inspections and enforcement actions at RCRA regulated facilities which is entered on an on-going basis. The BRS contains data collected biennially (for odd years) on the generation and management of hazardous waste by facilities. However, only large quantity generators (LQGs) and facilities that store, treat, or dispose hazardous waste (TSDFs) are required to complete a Biennial Report.[17]

In terms of the analysis period, it is important to make sure that it is long enough to get a complete picture of the timing of inspections. As reported in Section 2, 70 percent of the hazardous waste facilities that were inspected over the 2006 to 2010 period were inspected only once. Thus it is critical to have a relatively long period of time for the analysis. However, I also want to make sure that I have a sufficiently large pool of facilities in the analysis and the longer the time period, the fewer the number of facilities that were regulated throughout that time period. To balance these two issues, I chose to restrict the analysis to inspections that occurred between January 1, 2000 and December 31, 2010.

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[17] A large quantity generator is any facility that generates more than 1,000 kg (2,200 lb) of hazardous waste per calendar month, or more than 1 kg (2.2 lb) of acutely hazardous waste per calendar month.

Between January 1, 2000 and December 31, 2010, 314,776 RCRA inspections were conducted at 90,252 unique facilities. First note that during this eleven-year period, only about 12% of the over 760,000 facilities in the RCRAInfo database were inspected. While this is partly due to the fact that a number of facilities listed in RCRAInfo are inactive, it is also the case that many facilities regulated under RCRA are very rarely, if ever, inspected. In particular, of the over 300,000 facilities identified as conditionally exempt hazardous waste generators, less than 77,000 were inspected during the 2000 to 2010 period.[18] Since the goal of this paper is to better understand the timing of inspections, I want to focus the analysis on facilities that actually are inspected. Thus I decided to limit the analysis to LQGs and TSDFs as these facilities are much more likely to be inspected. Additionally, to ensure that the facilities in the analysis are actively regulated for the entire period of the analysis, I further limit the analysis to facilities that consistently reported to the BRS throughout this time period.[19] Of course, some facilities that do not consistently report to the BRS may be regulated throughout the period, but may fall out of or into the LQG or TSDF category during the analysis. Unfortunately these facilities are excluded from the analysis.

According to the BRS, 57,545 unique facilities filed biennial reports for at least one of the odd-numbered years between 1999 and 2009.[20] Of those facilities, 6,711 facilities filed reports for all of the odd years 1999-2009. Although the requirement that facilities consistently file BRS reports significantly decreases the universe for this analysis, I think it is important to ensure that facilities are active and eligible for inspections for the entire period of the analysis. Of the 6,711 facilities, 107 have no inspections recorded in RCRAInfo. Of the remaining 6,604 facilities, only 6,430 are inspected during the 2000-2010

[18] Conditionally exempt generators generate less than 100 kg (220 lb) of hazardous waste, or less than 1 kg (2.2 lb) of acutely hazardous waste, per calendar month. These facilities are subject to many fewer regulations than facilities that generate larger quantities of hazardous waste.

[19] Including facilities that are not subject to inspections in the analysis would systematically bias the results of the inspection timing analysis. However, RCRAInfo does not provide information on when facilities "enter" or "exit" the regulated universe.

[20] Since biennial reports are filed only for the odd years, I use information from the 1999 reporting cycle to infer that a facility was active in 2000 and from the 2009 cycle to infer that a facility was active in 2010. (The 2011 BRS data has not yet been released to the public.)

period. These facilities account for 59,480 inspections over that period (approximately 9 inspections per facility) which is almost 20% of all RCRA inspections conducted during that period even though they make up only about one percent of the regulated universe.

Approximately 95 percent of the inspections in RCRAInfo identify one type of inspection and one inspecting agency. The remaining records identify multiple purposes for the inspection and/or multiple agencies involved in the inspection. For those records, I created an inspection type hierarchy and an inspection agency hierarchy and then assigned both a primary inspection type and a primary inspection agency to each inspection based on those hierarchies. (Details on the hierarchies are provided in Appendix A.) Using the primary inspection types, I then determined whether the inspection should be considered a compliance inspection for the purposes of this analysis. In particular, I exclude inspections whose primary type is a facility self-disclosure, compliance assistance visit, case development inspection, or financial or non-financial record review from the analysis.[21] When these inspections are excluded, there are 43,559 compliance inspections in the initial dataset.

In a duration analysis, observations are spells, not inspections. To create the spell dataset for the analysis I used the *snapspan* and *stset* commands in Stata to convert the inspection data to spell observations that can be used to conduct the duration analysis. The analysis includes spells that are both left- and right-censored, that is spells that begin before the period of the analysis but end during the analysis and spells that begin during the period of the analysis but end after the period of the analysis. Dropping censored observations might lead to underestimates of spell length if censored spells are likely to be of longer duration than uncensored spells. Including censored spells increases the total number of observations in the dataset to 45,219.

Table 1 presents the explanatory variables used in the analysis along with a brief description of each variable, its mean, and its standard deviation. These data come primarily from RCRAInfo and the BRS. Note that there are three types of explanatory variables in the analysis: spell-specific data; facility characteristics; and state

[21] Most of these excluded inspections represent a small percentage of total inspections. However, financial and non-financial record reviews represent about 20 percent of all inspections.

characteristics. The first set of spell specific-variables identifies the type of inspection that ends the spell. Because compliance evaluation inspections are the most common type of inspection, I exclude this category from the regression and the spell duration of all other types of inspections is compared against the baseline duration of compliance evaluation inspections. I have no *ex ante* expectations about the signs of the coefficients on these variables. The next set of dummy variables identifies the lead agency in the inspection with the *State Lead* variable excluded from the regressions. For these variables I also have no initial expectations as to the sign of the coefficients. The final spell-specific variable is *Citizen Complaint* which indicates whether the inspection was the result of a citizen compliant. Here I do expect citizen complaints to shorten the duration of a spell and thus I expect a positive coefficient on this variable as a positive coefficient indicates a higher hazard ratio.[22]

Next consider the facility characteristics. A number of these explanatory variables are fixed and thus are the same across all spell observations at a given facility as well as across the entire period of the analysis. For example *TSDF* and *Commercial TSDF* indicate whether the facility treats, stores, or disposes hazardous waste and whether such services are sold commercially by the facility, respectively. Given that RCRA policies require TSDFs to be inspected at least once every two years, I expect positive coefficients on these variables. The variable *Used Oil* indicates whether the facility manages used oil in any way. Used oil is regulated separately from other hazardous wastes and suggests, *ceteris paribus*, a more complex facility. Similarly *Multimedia* indicates whether the facility is regulated under any other federal EPA programs. I expect positive coefficients for both of these variables as well.

The next three variables are all based on the primary industrial classification listed for each facility in RCRAInfo. *Waste Management* is equal to 1 if the facility's primary NAICS is 562; *Public Administration* is equal to 1 if the facility's primary NAICS is 92; and *Manufacturing* is equal to 1 if the facility's primary NAICS is 31 through 33. Because

[22] The results of a duration model may also be presented in terms of the hazard ratio. Positive coefficients correspond with hazard ratios that are greater than 1 (i.e., and increase in the hazard) and negative coefficients correspond with hazard ratios that are less than one.

federal and state operated facilities are supposed to be inspected at least once a year according to RCRA guidance, I expect a positive coefficient on *Public Administration*. I have no prior expectations as to the signs on the other two variables.

The remaining facility characteristics do depend on the date on which the spell starts but they do not vary across the spell itself. *Tons Generated*, *Tons Managed*, and *Tons Received from Off-Site* measure the tons generated, managed, and received from off-site, respectively, in the year prior to the spell's start date. Since BRS data is only reported in odd years, for even years I interpolated the quantities. Thus for a spell that begins in 2002, the variables are taken from the 2001 BRS while for a spell that begins in 2003, the variables are based on the mean of the quantities in 2001 and 2003. Because the quantities of waste generated, managed, and received have a skewed distribution, I use the log of tons rather than tons. I expect that all three of these variables will have positive coefficients.

Prior Year Inspections, *Prior 5 Year Inspections*, *Prior Year Violations,* and *Prior 5 Year Violations* measure the number of inspections and violations in the 12 months and 60 months immediately prior to the beginning of the spell. Note that for these counts, I only included compliance inspections, that is, the same type of inspections included in the overall dataset. However, I did include all violations discovered during the 12-month and 60-month time periods, regardless of whether those violations were discovered during a compliance inspection. I expect the two violation variables to have positive coefficients as less compliant facilities are more likely to be inspected in the future. I also expect that facilities that have been heavily inspected over a five-year period will continue to be inspected more often. However, controlling for the long-term level of inspection targeting, one might expect inspections in the prior year to increase the duration of the spell, particularly if annual inspections are relatively unlikely.

There are two state characteristics that also depend on the date on which the spell starts. *State Inspections* and *State Violations* measure the number of inspections and violations in the state, respectively, for the calendar year prior to the start of the spell. Both of these variables are normalized by the total number of RCRA facilities in the state. While I expect a positive coefficient on *State Inspections* as more inspections should shorten the duration of a spell, I expect a negative coefficient on *State Violations* as more violations will likely shift resources away from compliance inspections to following up on the detected violations. The remaining three state variables are based on 2005 data and are included to control for other differences across the state, but I have no expectations as to the sign of the coefficients on these variables.[23]

5. Comparative Results of the Duration Models

Kaplan-Meier Estimation Results

As discussed in Section 3, the Kaplan-Meier estimator is a nonparametric estimator of the survivor function. Figure 3 presents the estimated survivor and hazard functions for the entire universe.[24] As this estimator only uses observed failure times, the resulting estimations are based on 42,880 complete spells at 6,430 facilities. Note that the hazard function in Figure 3 is generally increasing in duration which would imply a positive duration dependence for the overall universe. More specifically, according to these results the longer the time since a facility has been inspected, the higher the probability of an inspection. Of course, this analysis ignores all information other than the length of time between inspections.

While the Kaplan-Meier estimator cannot take any independent variables into account, it is possible split the universe into different subsets and estimate survivor and hazard rates for the subsets. One can also test to see whether differences between estimated hazard rates are statistically significant. Figure 4 presents the estimated hazard rates for facilities that do and do not classify as TSDFs. Note that for both subgroups there continues to be some positive duration dependence although it is less pronounced than that estimated for the entire universe. Additionally, using a log-rank test I can reject the null hypothesis that the survivor functions are equal across TSDF. Moreover, using the log rank test, I can reject the equality of survivor functions across each binary or categorical variable with the exception of *Citizen Complaint*.[25] This suggests that the duration analysis

[23] State per capita income and GDP in 2005 were collected from the Bureau of Economic Analysis. State Environmental Organizations in 2005 is taken from the National Center for Charitable Statistics' Guidestar Database.
[24] The hazard function is estimated using a Nelson-Aalen cumulative hazard estimator and smoothing the steps using a Gaussian kernel function.
[25] Results available from the author upon request.

needs to take these variables into account, and thus the Kaplan-Meier model is unlikely to be the best model for analyzing inspection timing.

<u>Cox Proportional Hazard Results</u>

As discussed in Section 3, the Cox proportional hazard model allows explanatory variables to multiplicatively shift the baseline hazard function without requiring one to specify a particular function for that baseline hazard. The baseline hazard function can be left unestimated or can be estimated using non-parametric methods. Because I use state-level data, I lose 489 observations from 48 RCRA facilities located in the District of Columbia, Puerto Rico, Guam, and the U.S. Virgin Islands. The results of the Cox proportional hazard model for the remaining 44,730 observations at 6,382 facilities are presented in Table 2. To control for multiple spells at the same facility, I estimate robust standard errors clustered by facility.

The coefficients for all of the inspection types are significant and positive indicating that if the purpose for the inspection is anything other than a standard compliance evaluation inspection, the hazard rate is higher and thus the duration of the spell shorter. Note also that most of the coefficients on the type of inspector are significant. When the federal EPA or one of its contractors leads the investigation, the duration is longer as indicated by the negative and significant coefficients. If the lead is a state contractor or a state oversight team, the duration is shorter than if the inspection is led by the standard state regulators. Additionally, local inspections also occur more quickly than state inspections. Interestingly, contrary to expectations, a citizen complaint significantly increases the time to inspection rather than decreases it. Perhaps the existence of a citizen compliant requires inspectors to prepare more fully for an inspection then they otherwise would.

Turning now to the facility-level variables, the positive and significant coefficient on *TSDF* indicates that the hazard rate is higher for facilities that store, treat, or dispose waste, than for generators that do not. However, the coefficient on *Commercial TSD*F is not significant nor is the coefficient on *Used Oil Facility*. Facilities that are regulated under other EPA programs in addition to RCRA – i.e., *Multimedia* facilities – have a lower hazard ratio than facilities only regulated under RCRA. If regulatory programs coordinate inspections, inspectors may want to space out inspections from various programs and thus have a longer time between inspections from any one program. Alternatively, if programs conduct joint inspections, it may take more time to schedule an inspection.

Note that both *Waste Management* and *Public Administration* have positive and significant coefficients. The first result is consistent with regulators being more likely to inspect facilities for whom waste management is their primary activity rather than facilities the generate hazardous waste as a by-product of their primary activity. This could also explain why the coefficient on *Commercial TSD*F is not significant, as one would expect commercial TSDFs to have waste management as their primary industrial classification. The positive coefficient on *Public Administration* is consistent with EPA policy that state and federal facilities be inspected every year. Whether or not a facility is a manufacturing facility does not appear to have a significant effect on spell duration.

In terms of the time-specific variables, all three of the quantity variables have positive and significant coefficients indicating that the larger a facility is, the shorter the time between inspections. This is consistent with inspectors prioritizing inspections at facilities with larger potential impacts on the environment. While the coefficients on both of the facility inspection variables are positive, only the coefficient on *Prior Year Inspections* is significant. Similarly, although the coefficients on both of the facility violation variables are positive, only the coefficient on *Prior 5 Year Violations* is significant. The positive coefficients on these variables are consistent with regulatory targeting – that is, regulators targeting facilities with poor compliance records and inspecting them with a higher frequency than generally compliant facilities.

The two time-specific state variables, *State Inspections* and *State Violations*, also have significant coefficients. As expected, the coefficient on *State Inspections* is positive indicating shorter spells in states with more inspections and the coefficient on *State Violations* is negative indicating that spells are longer in states that have more violations per facility and thus have to spend more resources enforcing those violations. The coefficient on *State Per Capita GDP* is also negative and significant indicating that spells in states with higher per capita GDP have a lower hazard rate. Finally, the results indicate that spells in states with higher numbers of registered environmental charities also have a lower hazard rate.

Figure 5 presents the estimated baseline hazard for the Cox proportional hazard model presented in Table 2. While it looks somewhat like the Kaplan Meier hazard estimate presented in Figure 2, it has a much more pronounced range over which the baseline hazard is decreasing.

<u>Parametric Model Results</u>

As discussed in Section 3, by making an initial assumption about the distribution of the hazard function, parametric models can use the data on spells more efficiently than non- and semi-parametric models. I considered four commonly used parametric models: Exponential, Weibull, Gompertz, and Log-Logistic. For all three models, I used the same explanatory variables as were used in the Cox model presented in Table 2 and I estimated robust standard errors clustered by facility. Qualitatively, the estimation results for the Exponential, Weibull, and Gompertz models were all quite consistent. Recall that the Exponential model assumes that the baseline hazard rate is constant while the Weibull and Gompertz models both have two distribution parameters, γ and α. However, if α equals 1 in the Weibull model it reduces to an Exponential model and α equals 0 in the Gompertz model, it also reduces to the Exponential model. The results for the Weibull model and the Gompertz model both fail to reject the null hypothesis that the baseline hazard function is constant. Thus I present only the results for the Exponential model in Table 3.[26]

The results are qualitatively very similar to the results presented in Table 2. There are only two significant changes. The first is that the coefficient *on Prior 5 Year Inspections* is now significant although it was not in the Cox model. However, the sizes of the coefficient and hazard rate are very similar across the two models. Second, note that the Exponential model includes a constant term although the Cox model did not. In the Cox model, the baseline hazard model is not estimated directly and thus there is no need to fit a constant term. In the Exponential model, the baseline hazard is estimated to be:

$$\lambda_0(t) = e^{\alpha}$$

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[26] The results for the Weibull and Gompertz models are available from the author upon request.

where α is the constant terms estimated by the model. Thus the baseline hazard in this model is exp(-6.25) $\simeq$ 0.002, or a 1 in 500 chance of an inspection each day, regardless of the number of days that have passed since the last inspection.

While the Exponential, Weibull, and Gompertz model are usually expressed in terms of the hazard rate, the Log-Logistic model is most easily interpreted an accelerated time-failure model where:

$$\ln\left(t_j\right) = \beta_0 + x_j\beta_x + u_j$$

and u_j is assumed to follow a logistic distribution.[27] The estimated coefficients have to be interpreted differently in for this model – positive coefficients indicate a longer spell duration while negative coefficients indicate a shorter one. (Recall that the coefficients presented in Tables 2 and 3 change the hazard rate and thus a positive coefficient indicates a higher hazard rate and a shorter spell.) Table 4 presents the results of the Log-Logisitic Model. Allowing for the different interpretations of the coefficients between the Exponential results and the Log-Logistic results, there are a number of important differences to note. First in the Exponential estimations locally led inspections have shorter durations than state led inspections but the opposite is true in this estimation as shown by the positive and significant coefficient on *Local Lead*. The same pattern holds for inspections conducted by *State Contractors* – a shorter duration according to the Exponential estimation but a longer duration according the Log-Logisitic estimation. Additional, in the Log-Logisitic model, citizen complaints do not have a significant effect on the duration of the spell.

With respect to facility characteristics there are also a number of discrepancies between the two models. First note that *Used Oil Facility* has a significant coefficient while *Multimedia* does not. The opposite is true in the Exponential estimation, although the estimated signs of the coefficients are consistent (i.e., opposite) across the two different

[27] The Exponential and Weibull models can also be interpreted as accelerated time-failure models, but the Gompertz cannot.

specifications. Additionally, neither *Prior Year Inspections* nor *Prior 5 Year Violations* has a significant coefficient in the Log-Logisitic model, although both have a significant coefficient in the Exponential model. Perhaps most importantly, the coefficient on *Tons Generated* is positive and significant indicating the facilities that generate more waste have a longer time between inspections – the opposite of the finding in the Exponential model. Finally, with respect to state characteristics in the Log-Logistic model, higher state per capita income leads to statistically longer spell duration while higher state per capita GDP has no significant effect. In the Exponential model, higher state per capita GDP leads to statistically longer spell duration while higher state per income GDP has no significant effect.

Given the significant differences between the results for the Exponential/Weibull/ Gompertz models compared to the Log-Logisitic, I use the Akaike Information Criterion (AIC) to determine which model is preferable. The AIC compares log-likelihoods of the models, adjusting for the number of parameters being fitted. For the parametric survival models, the AIC is defined as:

$$\text{AIC} = -2\ln L + 2(k + c)$$

where k is the number of explanatory variables and c is the number of model-specific distributional parameters. A lower AIC indicates a better fit. As shown in Table 5, the Exponential, Weibull, and Gompertz models have virtually the same AIC and all have a much lower AIC than the Log-Logistic. Since the Exponential model is very straightforward and performs almost as well as the more complicated Weibull and Gompertz models, I have chosen to use it for the next stage of the analysis.

6. Comparison of Duration Model to Other Inspection Models

To better understand how well the Exponential model predicts inspections, I first estimated the mean predicted spell length for each observation in the duration database using the Exponential model presented in Table 3. Recall that each observation begins when an inspection occurs and the spell length is the time until the next inspection. The mean predicted spell length is calculated as the integral of the survivor function from zero to infinity given each observation's explanatory variables and the estimated model parameters. Figure 6 shows the mean predicted spell length plotted against the actual spell length with the dark line indicating the 45 degree line. Note that the model is not particularly good at predicting relatively long spells, and that the difference between the actual and predicted spells is often well over a year. This point is demonstrated more explicitly in Figure 7 which provides a frequency distribution of the difference between the actual and mean predicted spell length. Given that there are almost 43,000 spells in the analysis, this graph shows that for approximately 23,000 spells the difference between the actual and the predicted mean spell length is over a year. Thus for some spells the Exponential model is not a good predictor of spell length. However, it is not clear whether it is a better predictor of inspection timing than more commonly used models of regulatory inspections.

As discussed in the introduction, most empirical analyses of enforcement and compliance generally estimate the likelihood of an inspection for a given time period or the number of inspections for a given time period, with the time period selected based on the type of data available. For RCRA, the most obvious time period is a year since data on waste generation and management is reported annually. To compare the predictions of the Exponential model to annual inspection models, I used the mean predicted spell length to create a database of predicted inspections and then used the expected inspection dates to create a count of the number of predicted inspections in each calendar year. Figure 8 plots the predicted inspections using the exponential mean compared to the actual inspections that take place each year. While there are some outliers, note that the model does a pretty good job of predicting the number of annual inspections, particularly as the number of inspections per year increases.

For comparison purposes, I chose to use a Tobit regression of the annual number of inspections conducted at regulated entities.[28] I constructed a database which contains the annual inspections conducted at each of the 6,382 regulated entities included in the exponential analysis for the eleven year period of 2000-2010, for a total of 70,202 entity-

[28] The Tobit regression, unlike a standard OLS regression, explicitly takes into account the fact that the number of inspections is truncated at 0.

year observations.[29] For explanatory variables, I included all of the facilty-specific and state-specific variables used in the exponential analysis, but since the analysis is an annual one, none of the spell-specific variables are included.[30] The results of this analysis are presented in Table 6. As shown in Figure 9, I also plotted the number of predicted inspections from the Tobit model compared to the actual inspections that take place each year. Comparing to Figure 8 to Figure 9, note that the Tobit model does not predict actual inspections as well as the Exponential model does. While the Exponential model correctly predicts the number of inspections for almost 60 percent of observations, the Tobit model is correct only about 20 percent of the time. If we consider predictions that are within one inspection of the actual number of inspections, the Exponential model gets 96 percent of predictions within this band, while the Tobit model only places 78 percent within this band. Thus the Exponential model appears to be a significant improvement on the Tobit model for predicted the number of inspections at a facility in any given year.

Many inspection models examine not the number of inspections, but rather whether any inspections are conducted over a certain period. Thus I also conducted a Probit analysis on whether or not any inspections were conducted at an entity in a calendar year. The results of this analysis are presented in Table 7. The same facility-specific and state-specific explanatory variables are used in this analysis as in the Tobit analysis presented in Table 6, but the dependent variable is a binary variable equal to 1 if any inspection occurred at the regulated entity in a given year. To compare the results of the Probit analysis to the Exponential analysis, I compared the predictions of each model to the actual inspections. Since the Probit model predicts a probability of inspection, for any observation where the predicted probability of an inspection was greater than 0.5, I credited the Probit model with a predicted inspection. Table 8 summarizes the accuracy of the Probit model as well as the Exponential model. As shown, the Probit model correctly

[29] While there were 6,430 entities in the initial database, recall that the Exponential model uses state-specific data, and thus 48 entities in DC, Puerto Rico, Guam, and the Virgin Islands were dropped from the analysis.

[30] In the Exponential analysis, there is a set of variables capturing the number of inspections and violations conducted at the facility in the 12 months and 5 years prior to the start of each spell. For the Tobit analysis I construct similar variables for the 12 months and 5 years prior to the start of each calendar year.

predicts 40,733 of the 43,968 entity-year observations where there is no inspection while the Exponential model only correctly predicts 33,012 of these observations. Thus the Probit model is a better predictor of situations where there is no inspection. However, the Exponential model is a better predictor of inspections, correctly predicting 13,891 of the 26,234 observations where an inspection occurs compared to 9,821 predicted by the Probit model. Overall, the Probit model is correct approximately 73% of the time while the Exponential model is correct about 67% of the time. However, which model is a "better" predictor depends on the relative importance of Type I and Type II errors. The Probit model results in about 23% Type II errors (i.e. false negatives where no inspection is predicted even though there actually is an inspection) but only 5% Type I errors (i.e. false positives where an inspection is predicted even though there is no inspection). On the other hand the Exponential model results in just under 18% Type II errors, but 16% Type one errors.

7. Discussion

The goal of this paper is to model the timing of compliance inspections at hazardous waste generators to determine whether more sophisticated modeling of compliance inspections could improve the empirical analysis of compliance and enforcement. This paper presents a first step in a larger project to try to determine the extent to which regulated entities are able to predict inspection timing and whether entities use such predictions strategically in their compliance decisions.

Based on my analysis, if one does want to take advantage of all of the information available about individual inspections and model inspections using a duration model, the Exponential model provides the best balance in terms of the explanatory power of the model and the simplicity of the model. Additionally, my analysis suggests that using information on individuals inspections can help make better predictions about the number of inspections that a regulated entity is likely to face in a given year. If all one cares about is whether any inspection occurred in a given time period, the benefits of using a duration model are less clear. While the Exponential model performs better than the Probit model in predicting which entities will be inspected, it also results in a higher number of "false positives" that is predicting an inspection when no inspection actually occurs.

The next step in this research project is to develop a method for determining how well regulated entities appear to predict compliance inspections. To do this, I will use the Exponential model predictions to categorize actual inspections either as "early" or "overdue" to see whether there is a significant difference in compliance across those types of inspections. If facilities are able to predict inspections and use such predictions to strategically invest in compliance only when an inspection is imminent, we would expect to see a higher rate of non-compliance when an inspection is early compared to compliance when an inspection is overdue.

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Table 1:
Description of Explanatory Variables

Variable Name	Description	Mean	SD
Spell-Specific Data			
Compliance Evaluation*	Dummy variables indicating the type of inspection.	0.72	0.45
Focused Inspection		0.17	0.38
O&M Inspection			
Compliance Schedule Evaluation		0.05	0.22
Follow-up Inspection		0.02	0.14
Groundwater Monitoring		0.01	0.11
Corrective Action Eval.		0.01	0.10
EPA Lead	Dummy variables indicating the type of inspector.	0.07	0.26
State Lead*		0.91	0.29
EPA Oversight		0.00	0.05
State Oversight		0.00	0.01
Local Lead		0.00	0.05
EPA Contractor		0.00	0.07
State Contractor		0.01	0.10
Citizen Complaint	=1 if the inspection due to a citizen compliant.	0.01	0.10
Facility Characteristics			
TSDF	= 1 if the facility treats, stores, or disposes of hazardous waste.	0.37	0.48
Commercial TSDF	=1 if the facility is sells treatment, storage, or disposal services.	0.24	0.43
Used Oil Facility	= 1 if the facility manages used oil.	0.12	0.33
Multimedia	= 1 if the facility is regulated under other EPA programs	0.89	0.32
Waste Management	= 1 if the facility's main industry is waste management.	0.25	0.43
Public Administration	= 1 if the facility's main industry is public administration.	0.05	0.22
Manufacturing	= 1 if the facility's main industry is manufacturing.	0.58	0.49
Tons Generated	= log of tons of waste generated in the calendar year prior to the start of the spell.	2.84	8.38
Tons Managed	= log of tons of waste managed in calendar year prior to the start of the spell.	-10.63	10.06
Tons Received from Offsite	= log of tons of waste received for management in the calendar year prior to the start of the spell.	-9.54	10.89

Variable Name	Description	Mean	SD
Prior Year Inspections	= number of inspections in the year prior to the start of the spell.	6.20	15.17
Prior 5 Year Inspections	= number of inspections in the 5 years prior to the start of the spell.	25.55	60.94
Prior Year Violations	= number of violations in the year prior to the start of the spell.	2.78	13.56
Prior 5 Year Violations	= number of violations in the 5 years prior to the start of the spell.	15.73	60.42
State Characteristics			
State Inspections	= total state inspections in the calendar year prior to the start of the spell, normalized by the number of RCRA facilities.	0.03	0.03
State Violations	= total state violations in the calendar year prior to the start of the spell, normalized by the number of RCRA facilities.	0.05	0.04
State Per Capita GDP	= state per capita gross domestic product in 2005, in thousands.	36.00	5.18
State Per Capita Income	= state per capita income in 2005, in thousands.	33.82	4.82
State Environmental Organizations	= number of registered environmental charities in the state in 2005 per thousand residents	0.11	0.13

*Category excluded from the regression.

Table 2: Results of the Cox Proportional Hazard Model

Variable	Coefficient	Standard Error†	Hazard Ratio
Focused Inspection	0.825**	0.066	2.281
O&M Inspection	0.830**	0.083	2.294
Compliance Schedule Evaluation	1.812**	0.044	6.123
Follow-up Inspection	1.375**	0.091	3.957
Groundwater Monitoring	0.585**	0.066	1.794
Corrective Action Eval.	1.032**	0.115	2.807
EPA Lead	-0.195**	0.024	0.823
EPA Oversight	0.060	0.120	1.062
State Oversight	0.507*	0.250	1.660
Local Lead	0.268**	0.093	1.308
EPA Contractor	-0.630**	0.046	0.533
State Contractor	0.379**	0.109	1.460
Citizen Complaint	-0.174**	0.062	0.841
TSDF	0.469**	0.058	1.599
Commercial TSDF	0.093	0.101	1.097
Used Oil Facility	0.074	0.086	1.076
Multimedia	-0.211**	0.035	0.810
Waste Management	0.385**	0.100	1.469
Public Administration	0.324**	0.063	1.383
Manufacturing	-0.031	0.037	0.969
Tons Generated	0.013**	0.002	1.013
Tons Managed	0.006**	0.002	1.006
Tons Received from Offsite	0.013**	0.004	1.014
Prior Year Inspections	0.039**	0.004	1.039
Prior 5 Year Inspections	0.001	0.001	1.001
Prior Year Violations	0.000	0.001	1.000
Prior 5 Year Violations	0.001**	0.000	1.001
State Inspections	5.577**	0.690	264.368
State Violations	-2.000**	0.300	0.135
State Per Capita GDP	-0.013*	0.006	0.987
State Per Capita Income	0.007	0.006	1.007
State Environmental Organizations	-0.201**	0.070	0.818

† Standard errors are clustered by facility.
** Significant at the 1% level; *Significant at the 5% level.

Table 3: Results of the Exponential Model

Variable	Coefficient	Standard Error†	Hazard Ratio
Focused Inspection	0.838**	0.066	2.311
O&M Inspection	0.818**	0.080	2.266
Compliance Schedule Evaluation	1.806**	0.043	6.086
Follow-up Inspection	1.398**	0.091	4.048
Groundwater Monitoring	0.587**	0.066	1.798
Corrective Action Eval.	1.019**	0.118	2.769
EPA Lead	-0.190**	0.024	0.827
EPA Oversight	0.025	0.123	1.025
State Oversight	0.699**	0.214	2.012
Local Lead	0.222**	0.091	1.249
EPA Contractor	-0.647**	0.047	0.524
State Contractor	0.348**	0.109	1.416
Citizen Complaint	-0.179**	0.062	0.839
TSDF	0.486**	0.058	1.626
Commercial TSDF	0.100	0.100	1.105
Used Oil Facility	0.067	0.084	1.069
Multimedia	-0.199**	0.035	0.819
Waste Management	0.385**	0.103	1.469
Public Administration	0.320**	0.064	1.377
Manufacturing	-0.032	0.038	0.968
Tons Generated	0.011**	0.002	1.011
Tons Managed	0.006**	0.002	1.006
Tons Received from Offsite	0.013**	0.004	1.013
Prior Year Inspections	0.035**	0.004	1.036
Prior 5 Year Inspections	0.002*	0.001	1.002
Prior Year Violations	0.000	0.001	1.000
Prior 5 Year Violations	0.001**	0.000	1.001
State Inspections	6.511**	0.684	672.623
State Violations	-1.893**	0.302	0.150
State Per Capita GDP	-0.011*	0.006	0.989
State Per Capita Income	0.005	0.006	1.005
State Environmental Organizations	-0.211**	0.069	0.809
Constant	-6.252**	0.161	

† Standard errors are clustered by facility.
** Significant at the 1% level; *Significant at the 5% level.

Table 4: Results of the Log-Logistic Model

Variable	Coefficient	Standard Error†
Focused Inspection	-0.784**	0.062
O&M Inspection	-0.535**	0.112
Compliance Schedule Evaluation	-2.267**	0.096
Follow-up Inspection	-1.357**	0.110
Groundwater Monitoring	-0.816**	0.132
Corrective Action Eval.	-0.815**	0.174
EPA Lead	0.135**	0.026
EPA Oversight	-0.131	0.261
State Oversight	-2.763**	0.267
Local Lead	0.149**	0.053
EPA Contractor	0.311**	0.050
State Contractor	0.085*	0.042
Citizen Complaint	-0.021	0.075
TSDF	-0.349**	0.044
Commercial TSDF	-0.054	0.057
Used Oil Facility	-0.150*	0.059
Multimedia	0.009	0.039
Waste Management	-0.120**	0.052
Public Administration	-0.247**	0.059
Manufacturing	-0.040	0.024
Tons Generated	0.038**	0.001
Tons Managed	-0.013**	0.001
Tons Received from Offsite	-0.006**	0.002
Prior Year Inspections	0.025	0.019
Prior 5 Year Inspections	-0.133*	0.010
Prior Year Violations	-0.000	0.001
Prior 5 Year Violations	-0.000	0.000
State Inspections	-6.155**	0.774
State Violations	1.701**	0.263
State Per Capita GDP	-0.004	0.004
State Per Capita Income	0.018**	0.004
State Environmental Organizations	0.378**	0.061
Constant	6.687**	0.099
Gamma	0.274**	0.008

† Standard errors are clustered by facility.
** Significant at the 1% level; *Significant at the 5% level.

Table 5: AIC Values for the Parametric Models

Model	Log Likelihood	k	c	AIC
Exponential	29,822	32	1	-59,578
Weibull	29,824	32	2	-59,581
Gompertz	29,876	32	2	-59,683
Log-Logistic	2,775	32	2	-5483

Table 6: Results of the Tobit Model of Annual Inspections

Variable	Coefficient	Standard Error†
TSDF	0.320**	0.069
Commercial TSDF	0.257**	0.094
Used Oil Facility	0.323**	0.145
Multimedia	0.157**	0.034
Waste Management	-0.051	0.100
Public Administration	0.530**	0.079
Manufacturing	0.002	0.034
Prior Year Tons Generated	0.007	0.010
Prior Year Tons Managed	0.006**	0.002
Prior Year Tons Received from Offsite	0.012**	0.004
Prior Year Inspections	0.459**	0.078
Prior 5 Year Inspections	0.076**	0.011
Prior Year Violations	-0.015**	0.003
Prior 5 Year Violations	-0.0004	0.0004
Prior Year State Inspections	14.624**	1.045
Prior Year State Violations	-4.088**	0.337
State Per Capita GDP	-0.025**	0.005
State Per Capita Income	-0.037**	0.006
State Environmental Organizations	0.056	0.072
Constant	-1.283**	0.139

† Standard errors are clustered by facility.
** Significant at the 1% level; *Significant at the 5% level.

Table 7: Results of the Probit Model of Annual Inspections

Variable	Coefficient	Standard Error†
TSDF	0.507**	0.038
Commercial TSDF	0.122**	0.059
Used Oil Facility	0.019	0.052
Multimedia	0.063**	0.018
Waste Management	-0.003	0.046
Public Administration	0.377**	0.041
Manufacturing	-0.012	0.017
Prior Year Tons Generated	0.018**	0.003
Prior Year Tons Managed	0.004**	0.001
Prior Year Tons Received from Offsite	0.014**	0.002
Prior Year Inspections	-0.114**	0.010
Prior 5 Year Inspections	0.078**	0.004
Prior Year Violations	0.001**	0.0007
Prior 5 Year Violations	-0.0003	0.0002
Prior Year State Inspections	11.238**	0.374
Prior Year State Violations	-2.025**	0.147
State Per Capita GDP	0.010**	0.003
State Per Capita Income	-0.016**	0.003
State Environmental Organizations	-0.094**	0.044
Constant	-0.474**	0.065

† Standard errors are clustered by facility.
** Significant at the 1% level; *Significant at the 5% level.

Table 8: Comparison of Probit and Exponential Model Results

Status	Actual Observations	Probit Model Predictions	Exponential Model Predictions
Entity Not Inspected	43,968	Not Insp.: 40,733 (58%)	Not Insp.: 33,012 (47%)
		Inspected: 3,235 (5%)	Inspected: 10,956 (16%)
Entity Inspected	26,234	Not Insp.: 16,413 (23%)	Not Insp.: 12,343 (18%)
		Inspected: 9,821 (14%)	Inspected: 13,891 (20%)

Figure 1: Breakdown of 2010 RCRA Inspections by Primary Inspection Type

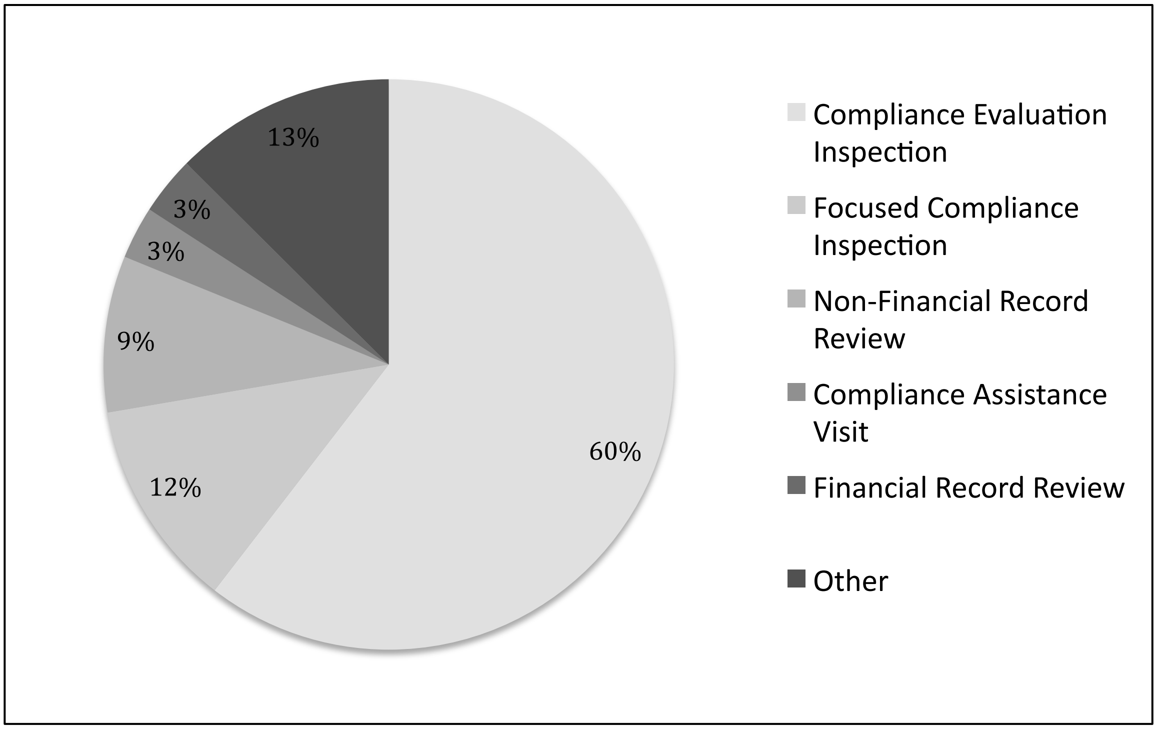


Figure 2: Breakdown of 2010 RCRA Inspections by Inspector Type

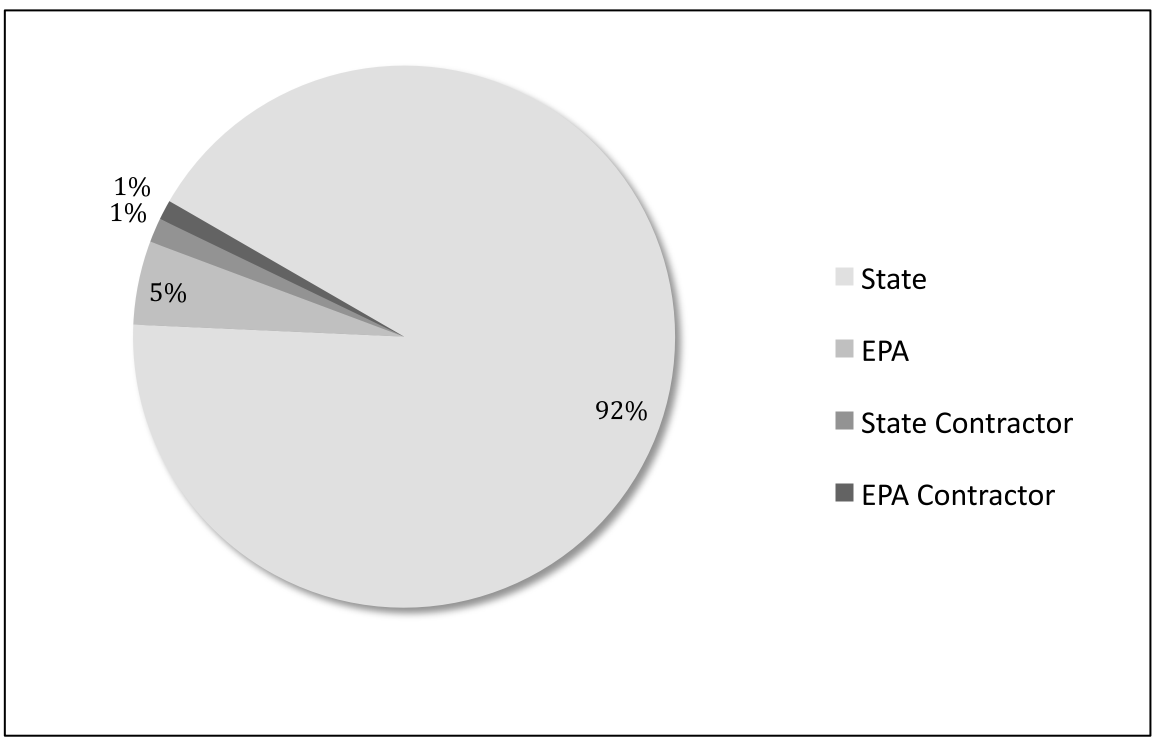
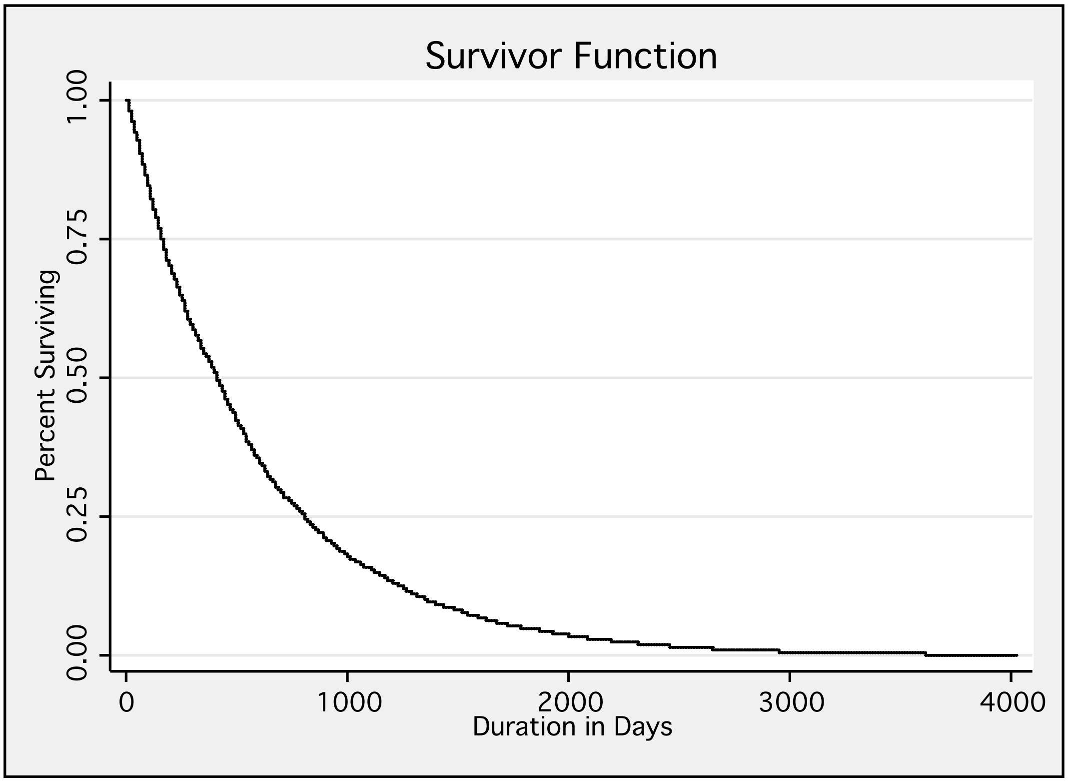


Figure 3: Kaplan-Meier Estimates for Complete Universe



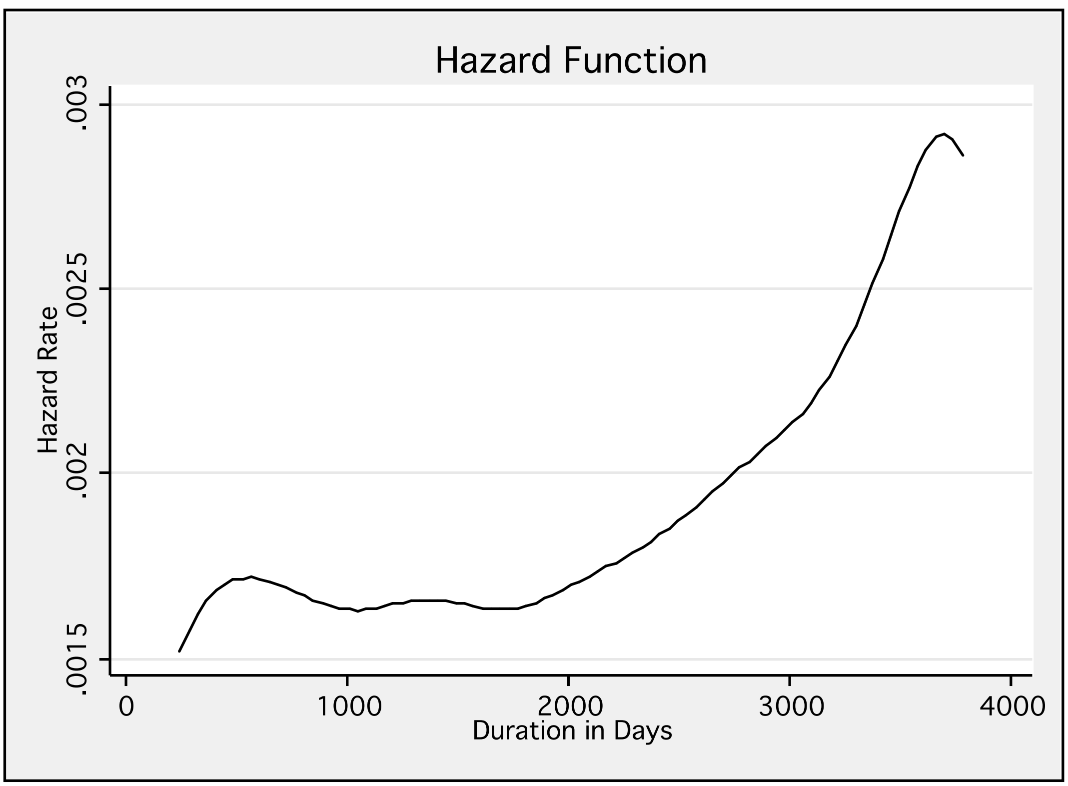


Figure 4: Non-Parametric Estimates for TSDFs and Non-TSDFs

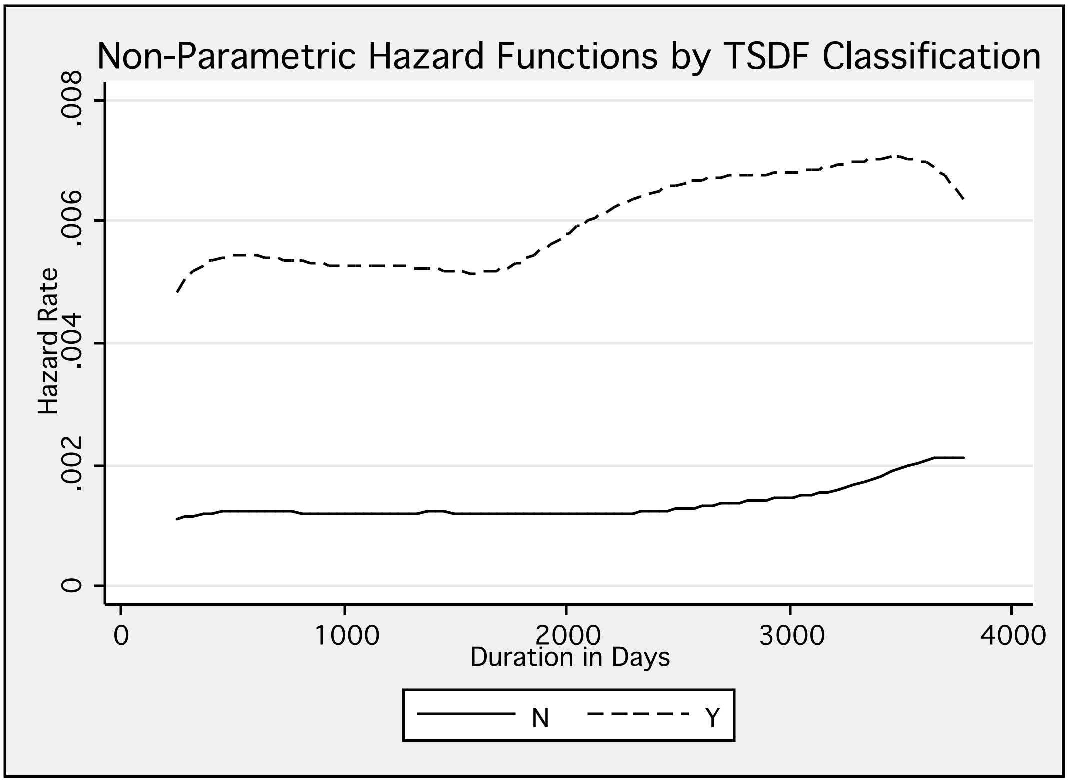


Figure 5: Estimated Baseline Hazard for the Cox Proportional Hazard Model

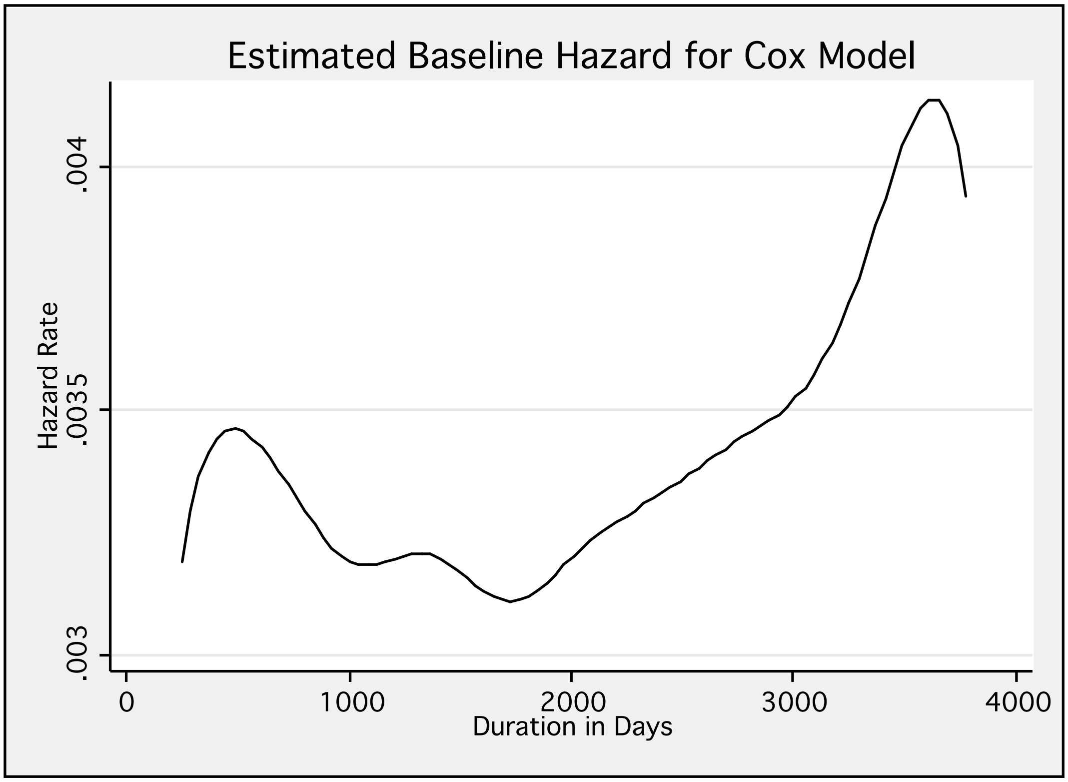


Figure 6: Mean Predicted Spell Length from Exponential Model

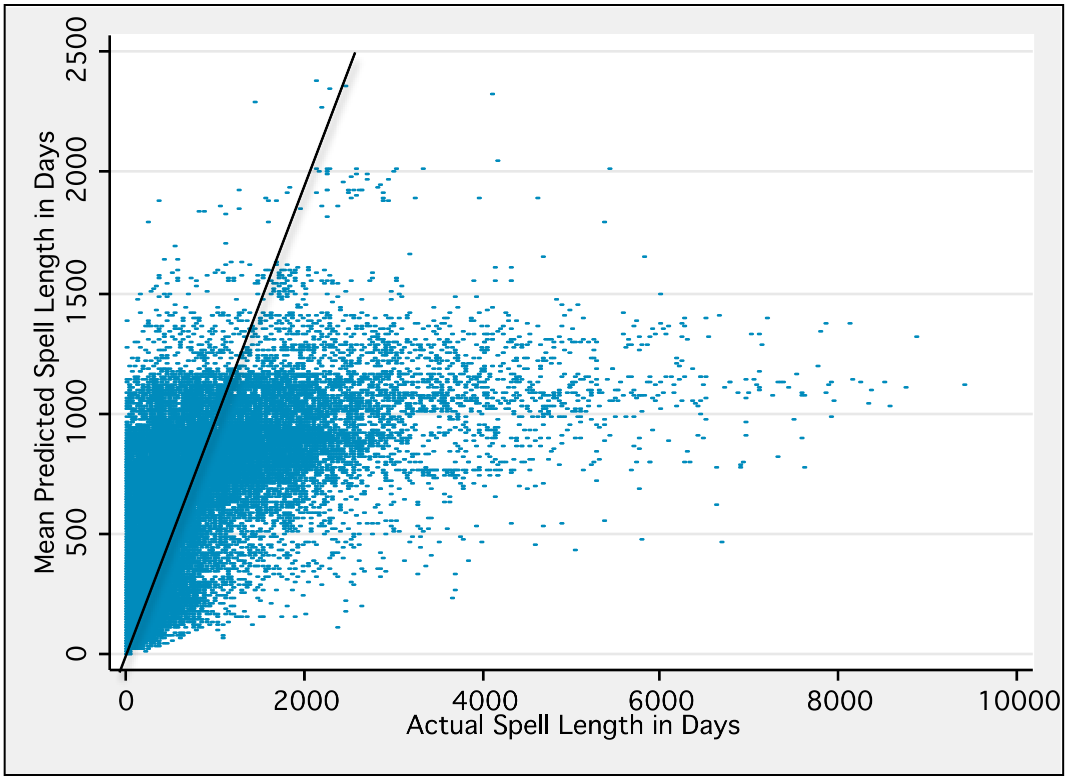


Figure 7: Distribution of Difference Between Actual and Mean Predicted Spell Length

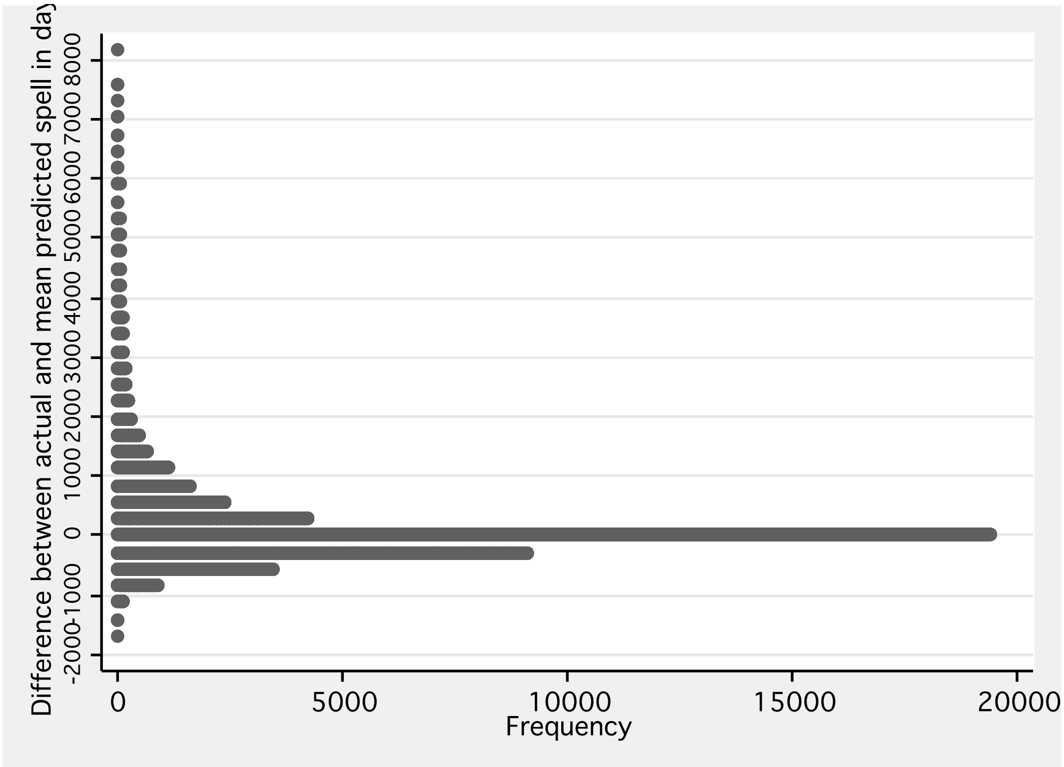


Figure 8: Predicted Annual Inspections from Exponential Model Compared to Actual Annual Inspections

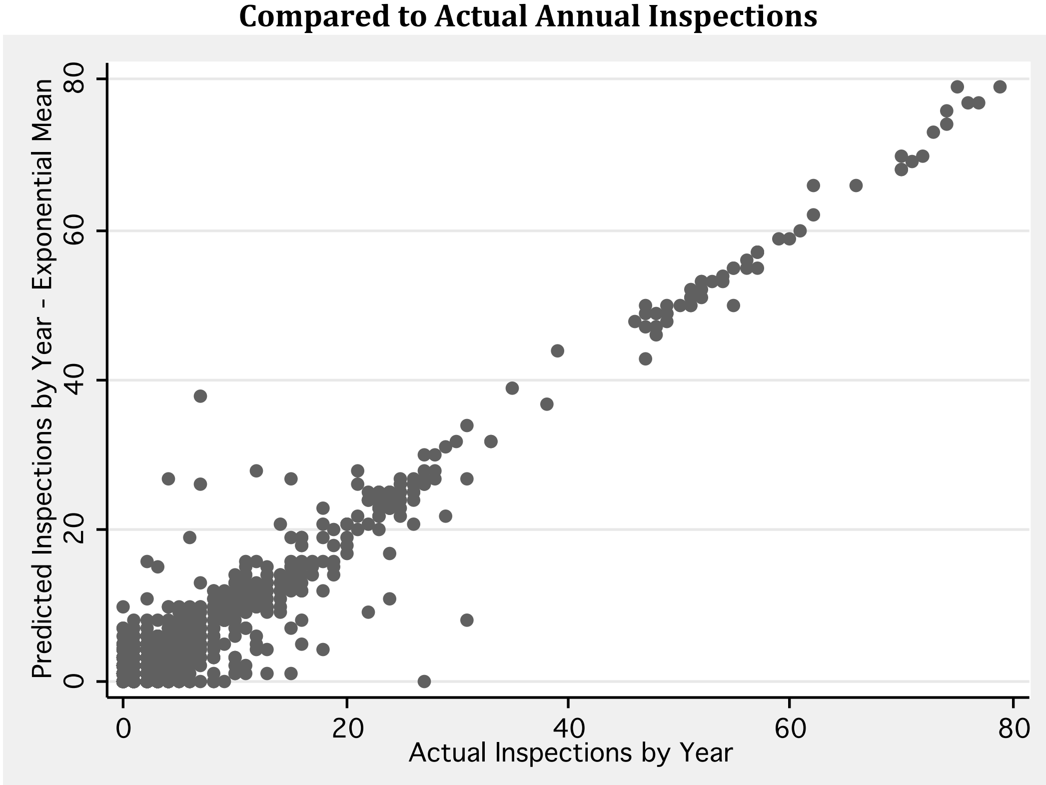
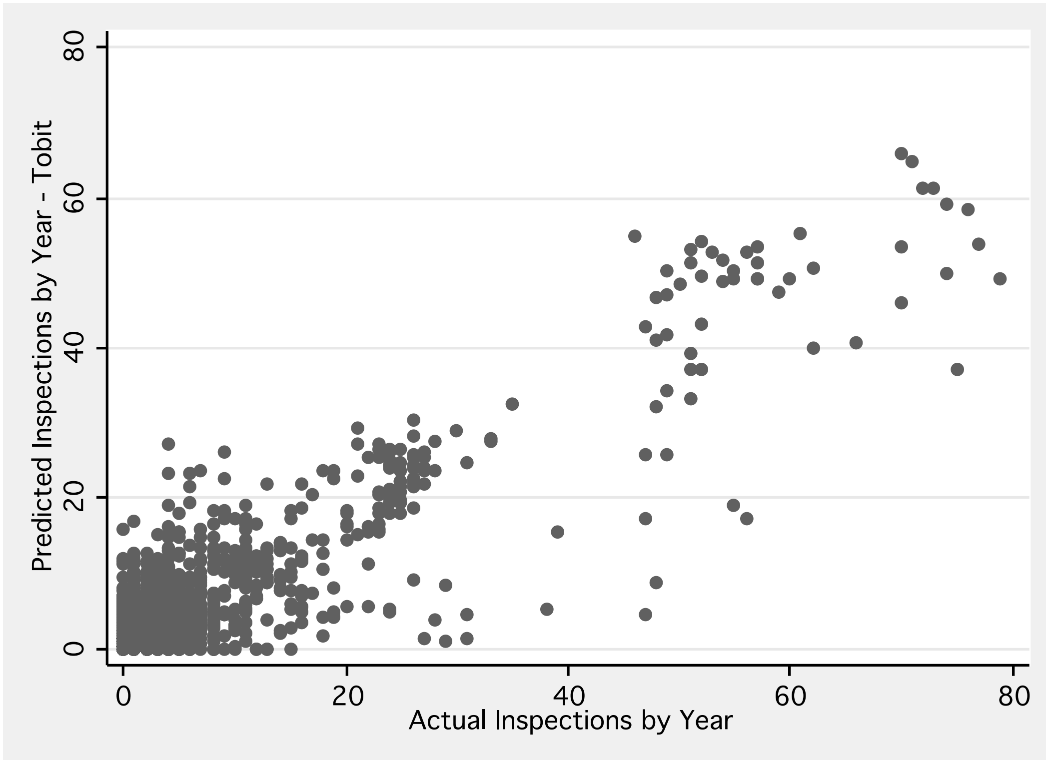


Figure 9: Predicted Annual Inspections from Tobit Model Compared to Actual Annual Inspections



Appendix A: Inspection Type and Inspection Agency Hierarchy

As discussed in Sections 2 and 4, each inspection event is identified by one or more inspection types and one or more inspections agencies. Over 95 percent of inspections list only one inspection type and one inspection agency. For the purpose of the analysis, I wanted to identify a primary type and primary agency for each inspection. First I created an inspection type hierarchy which ranks the various purposes based on their focus on compliance evaluation. The lists below shows the hierarchy of types and agencies, respectively, that I created as well as the fraction of total records and primary types each purpose represents. Note that the frequency of types is roughly equivalent across all records and across primary types.

Rank	Type of Inspection	Percentage of All Records	Percentage of Primary Types
1	Compliance Evaluation Inspection, On-Site	54%	55%
2	Focused Compliance Inspection	13%	12%
3	Operation And Maintenance Inspection	<1%	<1%
4	Compliance Schedule Evaluation	7%	7%
5	Follow-Up Inspection	2%	1%
6	Groundwater Monitoring Evaluation	<1%	<1%
7	Corrective Action Compliance Evaluation	<1%	<1%
8	Non-Financial Record Review	11%	11%
9	Financial Record Review	2%	4%
10	Case Development Inspection	<1%	<1%
11	Facility Self Disclosure	<1%	<1%
12	Compliance Assistance Visit	3%	3%
13	No 3007 Information Request Received	<1%	<1%
14	Significant Non-Complier	2%	2%
15	Not A Significant Non-Complier	2%	2%

Rank	Type of Agency	Percentage of All Records	Percentage of Primary Types
1	Federal EPA	6%	6%
2	State Regulator	90%	91%
3	EPA Initiated Oversight	<1%	<1%
4	State Initiated Oversight	<1%	<1%
5	Local	<1%	<1%
6	EPA Contractor	1%	1%
7	State Contractor	1%	1%
8	Tribal Authority	<1%	<1%