Environmental Violations in China: Evaluating Their Long-term Impact and Predicting Future Violations

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We take a business analytic approach to examine ways to reduce environmental incidents committed by Chinese manufacturers. We first perform *descriptive analysis* to examine the long-term impact of environmental incidents on a firm's performance that is measured in terms of Returns On Assets (ROA). By considering *all* 1542 environmental incidents occurred between 2004 and 2013 committed by 418 public Chinese manufacturing firms listed on Shanghai/Shenzhen Stock Exchange, we find empirical evidence that, relative to comparable firms without (any exposed) environmental incidents, firms with (exposed) environmental incidents have a lower ROA in consecutive years "only after" they were exposed. Despite the negative financial returns for being exposed, we speculate that low probability of being selected for inspection can be one of the key reasons for unethical Chinese manufacturers to violate environmental regulations. This speculation motivates us to use publicly available financial data to identify factors (e.g., age of the firm, total assets, percentage of government ownership, past environmental incidents) that one can use to *predict* which firm is more likely to violate environmental regulations. By using our training samples (from 2004-2012), we first develop our predictive model. Then we develop a scoring system to characterize the likelihood of a Chinese firm violating environmental regulations in 2013. By using these risk scores, we show the government can expose over 71% of the environmental violations in 2013 by inspecting only 21.5% of the firms with risk scores above the top 80 percentile. Therefore, our analytical approach has the potential to be used as a building block for the Chinese government to develop a more effective mechanism to select firms for inspection to expose non-compliance firms. With a higher chance of getting caught along with a harsher penalty imposed by the Chinese government since 2014, the number of environmental incidents in China is more likely to decline.

Keywords: Environmental Incidents, China, Business Analytics, Social Responsibility

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1. Introduction

China experienced a phenomenal economic growth: the GDP of China (in USD) grew from 395 billion in 1990 to 8,560 billion in 2012. To propel economic growth, the Chinese government reduced the penalty for violating environmental regulations over this 22-year period. Besides China's economic growth, we witnessed severe environmental problems caused by Chinese manufacturers who violated regulations by polluting air and water. Zhang et al. (2014) report that air pollution severely increases mortality from cardiovascular disease in China and shorten the lifespan of people living in Northern part of China by 5.5 years (Chen et al. 2013). In addition, over one-fifth of the China's rivers are toxic (Miao et al. 2015, Yang 2012). In the last decade, the Chinese government demonstrated their commitment to reduce pollution and improve environmental sustainability.[2] President Xi Jinping declared wars on environmental pollutions by imposing severe penalty for polluting the environment in late 2013. For example, the maximum penalty of discharging pollutants to sea without proper treatment has been increased from 100,000 RMB in 2014 to 1 million RMB in 2018. At the same time, the Chinese government is increasing its inspection effort to expose Chinese manufacturers who violate environmental regulations.[3]

In our opinion, the Chinese government's efforts (i.e., inspection and harsher punishment) are set in the right direction for reducing environmental incidents. However, to improve the effectiveness of these efforts, there is a need to develop a better understanding about the financial impact of environmental

[2] China's 13th five-year (2016-2020) plan (2016) emphases a lot on sustainable development; there is even a separate chapter call "Accelerating the improvement of the ecological environment," which provides detail plans on solving pollution problems and developing environmental sustainability in China.

[3] The Chinese government requires fifteen thousand factories to report real-time air emissions and water discharges figures to the public since 2014 (Albert and Xu 2016, Denyer 2014). The government also depends on public complaints or random check to conduct the environmental monitoring, which might not be an effective and efficient way (Dasgupta and Wheeler 1997).

incidents. For example, if the financial impact is relatively small and the 1 million RMB penalty is relatively low for major Chinese firms, then the government should reconsider its penalty. Also, to increase the chance of catching a violating firm, there is a need to develop an effective selection mechanism for the government to focus on firms with higher likelihood of committing environmental violations especially when the budget and manpower for inspection are limited. If the Chinese government can develop effective ways to increase the probability of catching violating firms and impose harsher penalty, then the number of environmental incidents is likely to decrease.

Motivating by the above observations and our own thought process, we take a business analytical approach to examine the environmental incidents in China observed between 2004 and 2013[4] by conducting the following analysis:

1. **(Descriptive Analysis)** What is the impact of an environmental incident on a firm's long-term financial performance (measured in terms of Returns on Assets (ROA)[5])? While Lo et al. (2018) conduct event studies to show that environmental incidents can cause the stock price of violating firms to decrease over the next day, we are interested in examining the long-term impact of these incidents on the firm's financial and operational performance (ROA) over the years. To conduct this analysis, we compare the ROA of "sample" firms (with exposed violations) against "matching" firms[6] (without exposed violations).

2. **(Predictive Analysis)** We consider publicly available information associated with different firms in different sectors including a firm's characteristics (age of the firm, percentage of

[4] We choose to focus on the year up till 2013 because the Chinese government changed its penalty in 2014. To avoid potential endogeneity issues, we focus on the data collected between 2004 and 2013.
[5] ROA is the most commonly used long term financial and operational indicators in operations management literature (e.g., Corbett et al. 2005, Hendricks and Singhal 2008, Lo et al. 2014). Following previous studies, the ROA is measured based on operating income over total assets. We use operating income *before* tax and interest expenses in our calculation, thus we can make sure the abnormal performance is only related to firms' operations.
[6] We use the propensity score matching method to identity comparable firms with the closest propensity score.

government ownership, past environmental incident history, etc.) and its past financial performance (total assets, debt ratio, financial leverage,[7] etc.). Which factors will exhibit predictive power for a firm's future environmental violations? For this predictive analysis, we develop a logistics regression model for predicting future environmental incidents.

3. **(Prescriptive Analysis)** By using our predictive model and the most recent publicly available information about each firm, we estimate the likelihood of a firm violating environmental regulation in the following year. Also, we prescribe a simple "greedy" sampling strategy that calls for inspecting firms in the order of higher likelihood of violations.

Our analysis yields the following results. First, relative to comparable firms (without exposed violations)[8], violating firms (with exposed violations) enjoy a higher ROA (0.51%) during the year "before" getting caught and suffer from a lower ROA (-0.66%) during the year "after" being caught. This finding has two implications. (a) For those violating firms (with exposed violations), they were operating at lower cost (and/or lower assets) without complying with the environmental regulations. However, once they were caught, they suffer from lower sales, higher cost, or higher assets as they take corrective measures. (b) Unless the chance of getting caught is sufficiently high (say, at least 50%) and the penalty is substantially high, unethical firms can afford to operate without complying with the environmental regulations. Therefore, to reduce environmental violations in China, the Chinese government needs to develop an effective audit/inspection mechanism to increase the chance of catching those violating firms.

Second, by using the data between 2004 and 2012 (the data for the year of 2013 is reserved as hold-out sample for validation), our logistics regression model reveals that: (a) firms with higher environment incidents in the past is more likely to continue to commit violations in the future; and (b) firms with higher revenue, larger assets, higher percentage of government ownership, and longer operating

[7] Debt ratio = Total liability/Total assets, and Financial leverage = Operating income/Net income.
[8] These are the firms who either comply with regulations or violate regulations without getting caught.

history have a higher tendency to violate environmental regulations. Finding (a) can be explained by the fact that the chance of getting caught was low and the penalty was relatively light. Hence, an effective inspection mechanism and a harsher penalty are necessary to reduce environmental incidents. Finding (b) characterizes the type of firms that tend to violate regulations, which can be useful for developing a more effective inspection mechanism.

Third, by using the results associated with the logistics regression model, we used the data from 2004 to 2012 to estimate the likelihood of each firm for violating regulations in the year of 2013. We find that, by inspecting 21% of all manufacturing firms (with the likelihood that is above the top 80 percentile), the Chinese government can catch 71% of those violating firms in 2013. More importantly, we show that, relative to a uniform random sampling approach (i.e., each firm has equal probability of being inspected), our "greedy" sample approach (i.e., firms are selected for inspection in the order of their likelihood) is much more effective for catching those violating firms than the random sampling method.

Overall, this paper contributes to the literature by examining the long-term impact of environmental incidents on a firm's financial performance (ROA), by establishing factors with predictive power for predicting future environmental incidents, and by prescribing a simple rule for selecting firms for inspection. While we focus our analysis in the Chinese context, our approach can be easily applied to examine other developing countries with severe environmental problems.

2. Literature Review

Our paper is related to two streams of literature. The first stream examines the relationship between environmental performance and financial performance. Recent event studies of environmental impact often found a positive correlation between environmental and financial performance. For example, Klassen and McLaughlin (1996) found a positive relationship between environmental award and firm's positive market performance and a negative relationship between environmental crisis and firm's negative market performance. Jacobs et al., (2010) found that "philanthropic gifts for environmental causes" and "ISO 14001 certifications" are positively related to firm's market performance, whereas "voluntary emission reductions" announcements are negatively related to firm's market performance. Similar findings had been found in developing countries. For example, Lo et al. (2018) found negative impact of environmental violations on firms' stock return in China. They further found that such negative impact diffuses downstream to the polluting firms' overseas customers one day after the pollution being exposed.

Despite the negative impact of environmental violations on firms' short-term stock price, operations managers are more likely to care about business and operational performance than stock price of the firm. In addition, the goal of environmental enhancement is always subordinate to other corporate goals as most businesses are profit driven (Arlow and Gannon 1982). There are some studies suggested a positive relationship between environmental performance and financial performance in the long run. For example, King and Lenox (2002) found that waste prevention and pollution reduction lead to financial gain. Lo et al. (2012) found that environmental management systems improve firm's long-term operational performance for the fashion and textiles related industries in the U.S. Our paper complements this stream of literature by examining the long-term impact of environmental violations in the Chinese manufacturers who operate under severe price competition with very thin profit margin.

Next, our paper is also related to the second research stream that deals with mitigation of environmental violations. Getting manufacturers to comply with environmental regulations is challenging for many reasons. First, because the actual cost of environmental violations is often indirect (e.g., drop in stock price), and occasional (i.e., depends on whether the violation is exposed), complying environmental regulations is rarely a top priority for most operations management who fight for business survival. Because of inconsistent inspections and law enforcement in many developing countries, and because many Chinese firms focus on short-term financial performance, creating incentives for social compliance (e.g., harsher penalty, more effective inspections) are critical for local government and global companies to be sustainable in the long run (Lee and Tang 2017).

Traditionally, government inspection is a commonly used coercive resolution for compliance in financial services (Pasiouras 2018), product quality (Ball et al. 2017), and corporate social performance (Tong et al., 2018). However, conducting compliance monitoring could be costly for governments in both developed and developing countries. In China, manufacturing firms self-report their pollution data in real-time or periodically, while the local governments then inspect the pollution cases[9]. However, firms' motivation to report accurate environmental data is low and thus the data are often not reliable (Brombal 2017). The three common issues of self-reporting are "messy data that lacks logic," "underreporting," and "delay reports" (Brombal 2017, Kostka 2016) are common among Chinese manufacturers.

Besides, local governments across China have no standard inspection process. IPE (2016) shows that the local governments only inspect 35.5% of those violation cases "self-reported" by the public manufacturing firms. In addition to inspecting those self-reported violations, China central government conducts random inspection as well (Ministry of Ecology and Environmental of the People's Republic of China [MEEPRC] 2018). To select firms for inspection, the government first classify firms into three inspection groups: *general pollution group*, *key pollution group*, and *special supervision group.* The special supervision group gets inspected most frequently at the rate of 1.39 times per year, and general pollution group and key pollution group are inspected 0.48 and 1.17 times per year, respectively (MEEPRC 2018).

The effectiveness of random inspection highly depends on available resources (e.g., budget, manpower, etc.). China government (MEEPRC 2108) has conducted 632.6 thousand inspections in 2017 and found 37.9 thousand violation cases. The average exposure rate is only 6% (= 37.9 /632.6). Also, China

[9] Example: Self-report real-time air emissions and water discharges system in Shandong Province. Please refer to http://58.56.98.78:8801/wryfb/MapMainT.html and http://58.56.98.78:8405

central government has invested 2.17 trillion RMB in the period of China's 12th five-year (2011-2015) plan, which was still far less than the expected environmental investment need (i.e., 3.4 trillion RMB) (Wu et al. 2016).[10] In view of limited budget and manpower for inspection, more advanced predictive approach is needed to minimize the risk of environmental pollution.

Predictive analytics has been applied in studying sports, epidemiology, supply chain development (Waller and Fawcett 2013), policing (Perry 2013), and firms' financial distress (Alan and Lapré 2018, Sarkar and Sriram 2001). Recently there are growing attention on applying predictive analytics on supply chain control. For example, Ball et al. (2017) used inspection records to predict a plant future quality risk. Caro et al. (2018) developed a prediction model to identify unauthorized subcontracting behavior of a global apparel supply chain. These recent studies all pointed to the need of predictive supply chain control,[11] and it should be an essential part during the big data era of global manufacturing (Schoenherr and Speier-Pero 2015). Our paper complements this stream of predictive supply chain control literature in the context of environmental violations in China. Specifically, we first develop a logistics regression model to identify factors that can be used to predict future environmental violations. Then we show how to use this prediction model to develop an effective selection mechanism for choosing certain firms for inspection that outperforms the baseline random inspection.

3. Sample and Data Collection

We conducted this research in the Chinese context because of the following reasons. Since its economic reform in 1978, China is facing severe environmental problems despite double-digit GDP growth for over

[10] For comparison, U.S Environmental Protection Agency (EPA)'s (2017) budget for inspection activities is USD 800 million in 2017, which is approximately 10% of the EPA's total budget (or 22% of total EPA staff).
[11] Predictive supply chain control refers to the management approach that uses predictive analytics to reduce the risk of disruptions in various supply chain contexts. Such as supplier relationships, product quality, logistics performance, and sustainability. Managing the risk of disruptions in these areas would enable organizations (e.g., sourcing firms and the host countries' governments) to reduce the risk of supply chain disruptions or catastrophic events that cost severe damages on environment and people health.

three decades (World Bank 2018). Therefore, by focusing on the environmental issues facing China, our study can be used as a reference for studying other developing countries (e.g., India) facing similar environmental challenges.

In addition to those sample firms used for examining the impact of environmental incidents on stock prices as discussed in Lo et al. (2018), we expanded our sample firms as follows. First, we sampled *all* 1,274 public manufacturing firms that listed on the Shanghai/Shenzhen A-share stock exchange in 2014. By examining these 1,274 firms, we obtained 9,574 firm-year observations between 2004 and 2013[12]. Second, we searched their environmental violations announcements between 2004 and 2013 from the Institute of Public and Environmental Affairs (ipe.org.cn) database and identified 1,590 environmental violations committed by 436 firms, which compose of 1,124 firm-year observations. Third, we collected their financial data from the Thomson Reuters Eikon database and firm's basic information (i.e., government ownership, firm age, and listed year) from the GTA's China Stock Market & Accounting Research (CSMAR) database.

After deleting the samples with missing data[13], we have a total of 8522 firm-year observations. These 8522 firm-year observations were divided into two groups: (a) 1082 firm-year observations involve exposed environmental violations (418 firms with 1542 environmental incidents); and (b) 7440 firm-year observations involve no exposed violations. The first group serves as our sample group and the second serves as the control group in our analysis. The financial characteristics of the aggregate 8522 firm-year observations and of those two groups of firms are provided in the top 3 blocks as shown in Table 1. Observe from Table 1 that those firm-year observations (with exposed environmental incidents) displayed in the second block tend to have larger assets, larger sales, higher net income, more employees, higher debt ratio,

[12] We excluded the delisted firms from our sample during this study period.
[13] We deleted sample firms with some missing data (i.e., government share of ownership, industry-adjusted ROA, or debt ratio) in their annual reports that are required for calculating the firm's operational and financial characters in Sections 4.1 and 5.1.

and higher financial leverage than those firm-year observations (without exposed environmental incidents) in the third block. This observation motivates us to consider using these financial characteristics as independent variables when we develop our predictive analysis in Section 5.

[Insert Table 1 here]

4. Descriptive Analysis: impact of environmental violations

In this section, we present a long-horizon event study approach to examine the causal effect of environmental violations on firm's performance (i.e., ROA). The main idea of the method is to detect abnormal performance by comparing the ROA performance of sample firms (with exposed violations) to that of control firms (without exposed violations). To develop a fair comparison by reducing selection bias, we used propensity score matching (PSM) to match each of those 1082 firm-year observations (second block in Table 1) with a control sample selecting from the 7440 firm-year observations (third block in Table 1) that face similar risk to having violations. (We describe the details about the way we compute the propensity score and how we match each sample firm with a control firm in Section 4.1.)

In our analysis, we define the "event year" (Year 0) as the year when the firm's environmental violation(s) were exposed. In doing so, Year 0 serves as the base year *t* for us to investigate the firm's pre- and post-event abnormal performance (in ROA). We set the pre-event period as the three years before the event (i.e., Year -3, Year -2, Year -1) and post-event period as the five years after the event (i.e., Year 1, Year 2, Year 3, Year 4, Year 5). The eight-year period is the most prolonged period we could investigate because the expansion of the year period will decrease the sample size dramatically. By noting that previous long-term event studies usually investigate a four-year period (see Hendricks and Singhal 2005, Lo et al. 2014, Liu et al. 2014), we believe our eight-year period is long enough to examine the causal relationship between environmental violations and firm's long-term financial performance.

For a sample firm with exposed violation observed in the base year t (i.e., year 0), We calculated its abnormal (ROA) performance (AP) in the year $t+j$ (year j is the ending observation year in our analysis with j = -2, -1,…,+5) by measuring the difference between the sample firm's actual (ROA) performance (SP) with exposed violations and its expected (ROA) performance without exposed violations (EP) in the year $t+j$; i.e.,

$$AP_{t+j} = SP_{t+j} - EP_{t+j}. \tag{1}$$

To compute the expected performance without exposed violations (EP) in the year $t+j$, we used the sample firm's actual (ROA) performance (SP) in the year $t+i$ (year i is the beginning observation year in our analysis with i = -3, -1,…,+4 and $i < j$) plus an "adjustment term" based on the change in the control firm's performance from year $t+i$ to $t+j$; i.e.,

$$EP_{t+j} = SP_{t+i} + \left(CP_{t+j} - CP_{t+i}\right). \tag{2}$$

Therefore, if environmental incident has no impact on ROA performance and if the sample firm's performance is similar to the control firm, then it is easy to check from (1) and (2) that abnormal (ROA) performance (AP) in the year $t+j$ is equal to 0. Therefore our analysis hinges on (a) finding a control firm without exposed violations to "match" each sample firm with exposed violations (b) examining whether the abnormal (ROA) performance of the sample firm is greater or less than 0. For (a), we used the propensity score matching approach as described in the next subsection. For (b), we conducted the t-test and Wilcoxon sign-rank (WSR) test to test whether the mean and median abnormal performance is significantly different from zero. We also conduct the binomial sign test to see whether the percentage of abnormal performance is significantly higher than 50%. We shall present our findings later in this section.

4.1. Propensity score matching for selecting control firms

To find a control firm without violations as a "comparable match" of a sample firm with violations require some careful analysis. Selecting a control firm with a similar risk of having violation(s) as the sample firm in a given year could result in self-selection bias (Dehejia and Wahba 2002). Previous research used dimension-to-dimension matching approach proposed by Barber and Lyon (1997) to match sample firms to control firms by a similar group of dimensions. However, it may also have "curse of dimensionality" due to the difficulties to match every dimension of sample firm to control firm (Ho et al. 2017). In many cases, researchers need to loosen the similarity standard for matching dimensions to ensure enough sample size, which may decrease matching quality. To eliminate the effects produced by these problems, we use the propensity score matching (PSM) that was first introduced by Rosenbaum and Rubin (1983) and widely used in the operations literature (Ho et al. 2017), economics literature (Dehejia and Wahba 2002) and healthcare literature (Crown 2014, Oh et al. 2017).

In our study, the propensity score is the firm's risk (estimated probability) of experiencing environmental violation(s) in an "observation" year.[14] We used the program Propensity Score Matching by SPSS, Version 3.0.4 (Thoemmes 2012) to calculate the propensity score for each of those 8522 firm-year observations (i.e., those firms included in the first block of Table 1). In our calculation, we considered observation year *(j)*, industry that a firm belongs to, firm's age by observation year *(j)*. Also, we included lagged independent variables that represent firms' operational and financial characters in year *(j-1)*, such as firm's revenue (in natural logarithm), total assets (in natural logarithm), industry-adjusted ROA, the percentage of government ownership, debt ratio and financial leverage. Then, for each of those 1082 firm-year observations (i.e., those firms with violations as stated in the second block of Table 1), we match this sample firm with a control firm (without exposed violations) from those 7440 firm-year observations (i.e., those firms included in the third block of Table 1) that has the closest propensity score in the same observation year.

[14] The propensity score is intended to identify control firms with similar risk than those sample firms in the "same" year. For this reason, it is less suitable than our logistics regression model (in Section 5) that uses data based on all "historical" years to predict each firm's likelihood for violating environmental regulations in future years.

With 1082 pairs of firm-year observations, we improve our matching quality by going through the following trimming process. First, to sure the sample firm and the (matched) control firm face similar operating environments and environmental regulations, we trimmed those pairs that belong to different industry. Second, we trimmed those pairs with dissimilar probability of having a violation in a given year; specifically, we removed those pairs that have a caliper[15] that exceeds 0.2 standard deviations (Austin 2011). Third, we trimmed those pairs when the matched control firm's revenue and total assets are not within a range of 95-105% of the sample firm's revenue and total assets (Quesnel-Vallee et al. 2010). Forth, we further eliminated pairs when the environmental incident did not indicate a specific incident, while our interests are the impact of a specific violation. Through these four steps, we have removed 361 pairs, resulting 721 pairs of sample firms and control firms with similar characteristics as presented in the fourth and the fifth blocks of Table 1.

4.3. Effect of environmental violations on long-term firm performance

By using (1) and (2) associated with those 721 matched pairs of sample and control firms, we can compute the abnormal (ROA) performance of each sample firm for year $t+j$ as discussed above. To examine the "long-term effect" of environmental incidents on a sample firm's performance, we examine the cumulative abnormal ROA performance over multiple years (i.e. year -3 to 0, year -2 to 0, and year -1 to 0) and post-event periods (i.e. year 0 to 1, year 0 to 2, year 0 to 3, year 0 to 4 and year 0 to 5), where year 0 is the base year t during which the incident occurred. We report the mean and median cumulative abnormal ROA performance in Figure 1, while we present our statistical test results in Table 2.

[Insert Figure 1 here]

[Insert Table 2 here]

[15] The caliper represents the probability difference between the sample and the matched firm of having a violation in a given year (Lunt 2013).

(A) **Abnormal ROA performance "before" the event year during which violations were exposed.** Observe the first column (year -3 to 0) in Table 2 that presents the cumulative abnormal ROA performance of sample firms between year -3 (i.e., 3 years prior to the exposed violations) to year 0 (i.e., the year of exposed violations). We find that the mean (median) of cumulative abnormal ROA from year -3 to 0 are 0.88% (0.46%), and it is significantly larger than zero (with $p < 0.01$ for the mean, and $p < 0.05$ for the median). Also, we find that 47.4% of the cumulative abnormal ROA performance associated with the sample firms are negative and they are significantly less than 50% ($p < 0.10$). Therefore, we can conclude that, relative to those matched control firms without exposed violations, sample firms with exposed violations enjoyed a higher ROA performance over the three-year period prior to the event year. (We also find similar results by observing the second column (year -2 to 0) and the third column (year -1 to 0). To avoid repetition, we omit the details.)

(B) **Abnormal ROA performance "after" the event year during which violations were exposed.** Observe the fourth column (year 0 to 1) in Table 2 that presents the cumulative abnormal ROA performance of sample firms between year 0 (i.e., the year of exposed violations) to year 1 (i.e., the year after the exposed violations). We find that the mean (median) of cumulative abnormal ROA from year 0 to 1 are -0.66% (-0.17%), and it is significantly larger than zero (with $p < 0.01$ for the mean, and $p < 0.05$ for the median). Also, we find that 52.1% of the cumulative abnormal ROA performance associated with the sample firms are negative, but they are not significantly higher than 50% ($p < 0.10$). Therefore, we can conclude that, relative to those matched control firms without exposed violations, sample firms with exposed violations suffered from a lower ROA performance over the year after the event year. (We also find similar results by observing the fifth column (year 0 to 2) and other columns. To avoid repetition, we omit the details.)

For robustness check, we conducted our analysis of the mean and median abnormal ROA performance of the sample firms on a "year-to-year" basis (instead of ROA performance over consecutive years). We obtain similar result as stated above. To avoid repetition, we provide the details in Appendix A.

In summary, by using the propensity score matching approach, we focus on 721 pairs of sample firms with exposed violations and control firms without exposed violations. By examining the cumulative abnormal ROA "before" and "after" the event year during which sample firms' violations were exposed, we find that sample firms with exposed violations tend to outperform control firms without exposed violations "before" the event year, but they perform much worse than control firms "after" the event years. Hence, there is economic incentive for violating environmental regulations if these sample firms were not caught; however, there is economic penalty if these sample firms were caught. Therefore, to reduce the tendency for firms to violate environmental regulations, the government needs to impose a harsher penalty for firms who violate environmental regulations, and to increase the chance of catching those non-complying firms. The Chinese government has increased the penalty to 1 million RMB, but it may not be harsh enough to deter large manufacturing firms to comply with the regulations. Also, with a limited budget and manpower as discussed earlier, the Chinese government needs to develop an efficient mechanism for selecting suspicious firms to inspect. This observation has motivated us to develop a predictive model to identify firms with a higher likelihood of violating regulations in the next section.

5. Predictive Analysis: factors for environmental violations

We now use the logistic regression modeling framework to develop our predictive model. Our logistics regression modeling choice can be justified as follows. First, our dependent output variable is a binary variable that indicates whether a firm has exposed violations in a given year, and our independent variables are based on the firm's characteristics and it financial performance. Second, logistic regression is superior to the decision tree for classification for sample smaller than 10,000 (Perlich et al. 2003). Third, the logistic regression model can indicate a possible causal relationship between the dependent variable and independent variables within a reasonable computing time. Fourth, other methods such as Naïve Bayes classifier, and artificial neural networks (ANNs) require additional time and procedures without improving the model accuracy and efficacy (Dreiseitl and Ohno-Machado 2002, Manel et al. 1999).

5.1. Logistics regression model analysis

As discussed in the last section, the intent of our predictive model is to classify firms according to their likelihood of violating regulations. Also, for practical purposes, we aim to develop our logistics regression model based on publicly available data from IPE website and firms' financial reports. Specifically, our logistics regression predictive model can be described as follows. First, our dependent variable $Y_{ij} = 1$ if firm *i* has exposed violations in year *j*, and $Y_{ij} = 0$, otherwise. Second, our independent variables are: incident history (firm *i's* total number of violations between 2004 and year *(j-1)* divided by the number of observations years), industry that firm *i* belongs to, firm's age by year *j*. Also, we include firm *i's* revenue in year *(j-1)* (in natural logarithm), total assets in year *(j-1)* (in natural logarithm), (industry-adjusted) ROA in year *(j-1)*, the percentage of government ownership in year *(j-1)*,[16] debt ratio (=total liability/total assets) and financial leverage (=operating income/net income) in year *(j-1)*.[17]

Our modeling framework is as follows. Firm *i* obtains a utility $V_{ij} + \varepsilon'_{ij}$ if it has exposed violations in year j, and obtains ε_{ij} if does not have any exposed violations in year j, where ε_{ij} and ε'_{ij} are error terms that are independent and identically distributed with a double exponential distribution. In this case, it is well known that the probability that firm *i* has exposed violations is given as:

$$P(Y_{ij} = 1) = \frac{e^{V_{ij}}}{1 + e^{V_{ij}}}, \qquad (3)$$

[16] Many firms used to be state-own enterprises and the Chinese government may continue to own certain shares of these firms as ways to assert certain influence on these firms.
[17] We have also tried other market-related factors such as debt-to-equity ratio, price-to-book ratio, gross margin, market share but they are not significant and do not improve the figures in model fit (i.e., 2 log likelihood, Cox & Snell R Square, Nagelkerke R Square) and the accuracy significantly. So, we did not include them in our model (see Appendix B).

which is a well-known result in discrete choice modeling (Anderson et al. 1992, Ben-Akiva and Lerman 1985). By using our independent variables as described earlier, the utility V_{ij} satisfies:

$$V_{ij} = \beta_0 + \beta_1 Incident\_history_{i(j-1)} + \beta_2 Industry_i + \beta_3 firm\_age_{ij} + \beta_4 Revenue_{i(j-1)} + \beta_5 Total\_assets_{i(j-1)} + \beta_6 ROA_{i(j-1)} + \beta_7 Goverment\_ownership_{i(j-1)} + \beta_8 Debt\_ratio_{i(j-1)} + \beta_9 Financial\_leverage_{i(j-1)} \quad (4)$$

To estimate the parameters associated with the above model, the likelihood of the training sample L (associated with 7306 firm-year observations between 2004 and 2012 as shown in Table 3, where the remaining 1216 firm-year observations in 2013 as holdout samples for validation later)[18] can be defined as: $L = \prod_{ij=1}^{7306} P(Y_{ij}) = \prod_{ij=1}^{7306} \left[\frac{e^{V_{ij}}}{1+e^{V_{ij}}}\right]^{y_{ij}} \left[1 - \frac{e^{V_{ij}}}{1+e^{V_{ij}}}\right]^{1-y_{ij}}$,

where *ij* represents the *ij*[th] observation. Then we can obtain the estimated parameters β_k, k = 0, 1, 2, …9, that maximize the likelihood L as defined.

[Insert Table 3 here]

By maximizing the likelihood function L as defined above, we can determine the estimated coefficients β_k, k = 0, 1, 2, …9, as stated in (4) and these estimated coefficients are reported in Table 4.

[Insert Table 4 here]

As shown in Table 4, we find that ***revenue*** and ***incident history*** are positively related to the emergence of environmental violations (both at p<0.01). Therefore, our model suggests that firms with more considerable revenue and a higher incident history in the past tend have a higher tendency of having exposed violations. Some other significant factors were the ***percentage of government ownership***, ***total assets***, and ***industry-***

[18] For robustness check, we also used (1) 6124 firm-year observations in the 2004-2011 period as a training set to predict the remaining 2398 observations in the 2012-2013 period, and (2) 6855 random-select firm-year observations (80%) to predict the remaining 1667 observations (20%). We obtained similar results. To avoid repetition, we focus our discussion for the analysis associated with those 7306 firm-year observations over 2004-2012 as the training samples, and treat those 1216 firm-year observations as holdout samples.

adjusted ROA (all at p<0.05). The result shows that firms with higher government ownership, larger total assets, and lower ROA have a higher tendency of having exposed violations in the future. Finally, we find that firms that are older (i.e., a higher ***firm age***) have a higher tendency of having exposed violations.

In summary, our results obtained from the logistics regression model enable us to identify certain factors (***firm age, total assets, percentage of government ownership, ROA, revenue, incident history***) that fit those firms with exposed violations between 2004 and 2012. Besides goodness of fit as shown in Table 4 and those factors that can affect a firm's tendency of having exposed violations, we can use our model via (3) to predict which of those 1216 firm-year observations in our holdout samples involve exposed violations in the year of 2013. We shall examine this issue next.

5.2. Predictive analysis

By using the estimated value of those significant coefficients as reported in Table 4 and the values of those significant of each firm *i* between 2004 and 2012, we can use (4) to compute the utility V_{ij} for each of those 1216 firms in year *2013* in our holdout sample (Table 3). Then we can apply (3) to compute $P(Y_{i,j=2013} = 1)$; i.e., the estimated probability of firm *i* having exposed violations in year 2013. Esssentially, the estimated probability $P(Y_{i,j=2013} = 1)$ is an estimated risk measure of firm i for having exposed violations in 2013. To examine the effectiveness of our predictive analysis via the "classification" probability $P(Y_{i,j=2013} = 1)$, we plot the receiver operating charateristic (ROC) curve for the training-test model (Figure 2). We plotted the True Positive Rate (TPR) at the X-axis against the False Positive Rate (FPR) at the Y-axis at various cut-off points (i.e. $P\left(Y_{i,j=2013} = 1\right)$ between 0 to 1). Specifically, TPR equals the number of "correctly" predicted firms having violations divided by the actual number of firms having violations exposed. Similarly, FPR equals the number of "incorrectly" predicted firms with exposed violations (but actually without exposed violation) divided by the actual number of firms that do not have exposed violations. The ROC curve represents the tradeoff between cost (i.e., FPR) and benefits (i.e., TPR) derived from our prediction model (Fawcett 2006). The curve skews towards top-left means the prediction of our model generates a better result than the random selection model (i.e., the straight line means the FPR and TPR were equal at all the cut-off points[19]). The area under the curve of our model is 0.844, which shows our prediction accuracy is higher comparing to the random model.

[Insert Figure 2 here]

To gain a better understanding of our risk measure, we trace those firms with $P(Y_{i,j=2013} = 1) > 0.5$. Out of those 1216 firms in our holdout sample, we find 82 firms with risk measure above 0.5 (Table 4). It is interested to observe from Table 5 that, among these 82 firms, 22 firms produce chemical products (C26, C28, C29). Also, another 22 firms produce metal and non-metallic mineral products (C30-C33). Knowing these types of firms have to deal with chemical and industrial waste, our risk measure appear to be reasonable in identifying these firms as "risky" in terms of having exposed violations in 2013.

[Insert Table 5 here]

As noted in Table 3, 100 firms out of 1216 firms (8% of our holdout sample in 2013) have exposed violations in 2013. It is interesting to see if we can use our risk measure $P(Y_{i,j=2013} = 1)$ to predict which of the 1216 firms have exposed violations in 2013. To do so, we sort those 1216 firms in our holdout sample according to the risk measure in descending order. We find that the firm with the highest risk probability $P(Y_{i,j=2013} = 1) = 0.9993$ was indeed the firm that had exposed violation in 2013. Similarly, the firm with the second highest risk probability $P(Y_{i,j=2013} = 1) =$

[19] For robustness check, we also reported the ROC curve of the prediction for our training-test model, using (1) 6124 firm-year observations in the 2004-2011 period as a training set to predict the remaining 2398 observations in the 2012-2013 period, and (2) 6855 random-select firm-year observations (80%) to predict the remaining 1667 observations (20%) in the Appendix C.

0.9969 was indeed the firm that had exposed violation. Therefore, the predictive power of those high-risk firms is rather strong. As we go down the list of these 1216 firms, the predictive power weakens (as shown in Figure 3). By comparing the predictive accuracy of our risk probability against the base probability of having 8% chance of selecting a firm with exposed violations, Figure 3 illustrates that our risk probability provides a more accurate prediction.

[Insert Figure 3 here]

5.2. Firm audit selection strategy

Knowing that our risk probability provides a better predictive power than the base probability of 8%, we now propose an audit selection strategy that can potentially be used by the government agency to catch those violating firms more effectively. First, we can use the risk probability to identify firms that lie within a certain range of risk probabilities (e.g., from 0.9 to 1.0, from 0.8 to 1.0, etc.). Then, with a limited manpower and budget, the agency can focus on those firms that lie within the higher range of risk probabilities. For example, as reported in Table 6, there are 13 firms with risk probabilities between 0.9 and 1.0. By auditing these 13 firms out of 1216 firms, the agency can catch 7 out of 100 violating firms in 2013. The "returns on investment" associated with this audit strategy is great for the agency: by auditing only 1.07% of those 1216 firms, the agency caught 7% of those 100 violating firms in 2013.

[Insert Table 5 here]

Similarly, observe from Table 6 that there are 82 firms with risk probabilities between 0.5 and 1.0. By auditing these 82 firms out of 1216 firms, the agency can catch 32 out of 100 violating firms. In this case, the “returns on investment” is great: by auditing only 6.7% of those 1216 firms, the agency caught 32% of those 100 violating firms in 2013.

By auditing firms with risk probabilities above a certain value, we can plot the returns on investment based on the % of those 1216 firms being audited and the % of those 100 violating firms being caught. This plot is provided in Figure 4. As shown in Figure 4, by using the proposed firm audit selection strategy, the agency can catch 80% of those 100 violating firms by auditing 32% of those 1216 firms in the holdout sample. If one uses a uniform sampling that each of the 1216 firms has equal probability of being selected for audit, then the agency needs to audit 80% of those 1216 firms to catch 80% of those 100 violating firms. As shown in Figure 4, our proposed firm audit selection strategy is quite efficient.

[Insert Figure 4 here]

In summary, we can conclude that, by using a simple audit selection strategy that focuses on auditing firms with high-risk probabilities, we can catch those violating firms by auditing a relatively small number of firms. This finding suggests that, when government has limited budget and manpower, our audit selection strategy can be an effective mechanism for increasing the chance of catching those violating firms. By increasing the chance of catching those violating firms and by imposing a harsher penalty for those violating firms, one can deter firms from violating environmental regulations. Therefore, our predictive model based on the logistics regression (3) and (4) and our risk probability can serve as a building block for developing effective firm audit selection strategy to deter firms from violating environmental regulations.

6. Discussion

We have used a business analytic approach to examine issues arising from environmental violations committed by publicly traded Chinese firms. First, while Lo et al. (2018) established empirical evidence that environmental incidents can reduce the stock market value of a firm in China, the impact of environmental incidents on the firm's financial ROA performance remained unclear. This observation has motivated us to compute the abnormal ROA performance of those sample firms with exposed violations and compare it against those control firms without exposed violations. Our comparison revealed that, relative to those comparable control firms selected through the use of the Propensity Score Matching approach, sample firms obtain a higher (lower) ROA before (after) the event year during which violations were exposed. This finding implies that there is economic incentive for violating environmental regulations until the firm is caught. Hence, unless there is a higher chance of getting caught and unless there is a harsh penalty for violations, there is an incentive for firms to violate regulations.

The above finding has motivated us to use the logistics regression modeling framework to develop a predictive model by using a firm's characteristics and historical financial performance to predict the risk probability of a firm has exposed violations in the future. Our logistics regression model enabled us to identify certain factors with predictive power. These factors include revenue, firm age, past ROA performance, percentage of government ownership, etc. To examine the performance of our predictive model, we compute the risk probability of each firm (i.e., the probability that the firm has exposed violations in the future year (i.e., 2013)). Our analysis revealed that firms with higher risk probability tend to be those firms with exposed violations in the future year. This finding helped us to propose a "greedy" firm audit selection strategy under which the agency should focus on firms with risk probability exceeding a certain value. By using our holdout sample in 2013, we have shown that the agency can catch 80% of those violating firms by auditing 32% of the holdout sample firms. This result suggested that our firm audit strategy is quite effective.

Overall, we hope our business analytic approach presented in this paper can be used as a building block for developing a more efficient firm audit strategy so that the government agency can catch those violating firms more effectively. First, our model can be enhanced by incorporating other data such as employment data (which include education level, labor turnover, etc.), manufacturing process data (which include input materials, manufacturing process, and output materials, etc.), education training data (which include environmental sustainability training programs, compliance programs, ISO 14000 certification programs, etc.). In addition to building a better model, the government agency can work with NGOs to monitor and audit firms, develop anonymous hotlines for encouraging workers and the public to report any suspicious water and air pollution in their factories and neighborhood. By combining an effective audit mechanism and by working with more stakeholders, the government can increase the chance of catching those violating firms. When the chance of being exposed is high and when the penalty is high, fewer firms would dare to violate environmental regulations. This way, China can become cleaner faster.

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Table 1. Descriptive statistics of the firm-year observations

	Total assets (RMB 000,000)	Sales (RMB 000,000)	Net income (RMB 000,000)	Number of employees (000)	ROA	Debt ratio	Financial leverage
All firm-year observations (*n* = 8522)							
Mean	5,146.03	4,373.85	264.18	4.31	0.05	0.51	1.32
Median	1,923.99	1,222.63	76.96	2.09	0.05	0.48	1.05
Std. error	14,004.59	14,228.10	1,178.08	8.08	0.09	0.70	14.53
Maximum	318,633.18	480,979.67	42,028.16	177.62	0.75	43.08	1,281.06
Minimum	14.77	0.00	-9,092.06	0.00	-4.95	0.00	-177.62
Firm-year observations with exposed violations (*n* = 1082)							
Mean	11,661.05	10,376.56	620.99	8.28	0.05	0.54	2.37
Median	3,677.83	2,661.19	133.92	3.51	0.05	0.54	1.08
Std. error	25,337.10	26,060.86	2,259.74	14.71	0.07	0.27	38.99
Maximum	318,633.18	434,803.95	42,028.16	177.62	0.52	4.46	1,281.06
Minimum	39.63	0.00	-9,092.06	0.02	-0.32	0.03	-27.15
Firm-year observations without exposed violations (*n* = 7440)							
Mean	4,198.55	3,500.88	212.29	3.73	0.05	0.51	1.16
Median	1,777.49	1,127.18	71.53	1.95	0.05	0.47	1.04
Std. error	11,148.82	11,277.71	909.11	6.38	0.10	0.74	4.55
Maximum	317,203.00	480,979.67	40,156.36	89.79	0.75	43.08	163.97
Minimum	14.77	0.40	-5,320.00	0.00	-4.95	0.00	-177.62
Final firm-year observations with exposed violations (*n* = 721, final sample firms in the observation years)							
Mean	9,701.23	8,024.07	493.76	7.41	0.05	0.54	1.24
Median	3,766.37	2,614.23	130.64	3.57	0.05	0.55	1.11
Std. error	19,347.04	16,766.22	1,418.12	12.35	0.06	0.31	2.55
Maximum	176,969.16	162,325.57	19,204.29	166.41	0.50	4.46	21.64
Minimum	266.87	47.59	-3,281.00	0.02	-0.30	0.07	-27.15
Final firm-year observations without exposed violations (*n* = 721, final matched control firms in the observation years)							
Mean	8,524.98	7,227.70	423.84	6.14	0.06	0.53	0.86
Median	3,445.24	2,421.10	124.48	3.29	0.05	0.54	1.11
Std. error	18,817.33	16,760.65	1,286.08	9.35	0.06	0.20	7.63
Maximum	220,875.84	200,638.01	15,652.19	89.79	0.51	2.00	25.10
Minimum	326.05	82.93	-5,320.00	0.03	-0.12	0.01	-177.62

Note. All the factors are based on the fiscal year ending before the observation year

Table 2. Cumulative abnormal ROA performance of sample firms

	Year -3 to 0	Year -2 to 0	Year -1 to 0	Year 0 to 1	Year 0 to 2	Year 0 to 3	Year 0 to 4	Year 0 to 5
n (number of observations)	719	721	721	721	719	716	638	541
Mean abnormal ROA	0.88%	0.59%	0.51%	-0.66%	-1.19%	-1.30%	-0.78%	-1.33%
t -statistic	2.49**	1.80*	2.18*	-2.53**	-4.10**	-3.91**	-2.15*	-3.13**
Median abnormal ROA	0.46%	0.38%	0.28%	-0.17%	-0.70%	-0.71%	-0.12%	-0.78%
Wilcoxon signed-rank *Z*-statistic	2.16*	1.58+	1.75*	-1.93*	-3.58**	-3.54**	-1.83*	-3.19**
% abnormal ROA (negative)	47.4%	47.4%	48.1%	52.1%	56.2%	55.4%	51.4%	54.2%
Binomial sign test *Z*-statistic	1.34+	1.34+	0.97	-1.12	-3.28**	-2.88**	-0.67	-1.89*

Note: + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$ (all tests are one-tailed).

Table 3. Number of sample firms by years

Year	Total number of firms	Number of firms with violations	% (Firms with violations)
2004	516	26	5%
2005	605	47	8%
2006	668	90	13%
2007	732	115	16%
2008	811	135	17%
2009	798	118	15%
2010	902	131	15%
2011	1,092	164	15%
2012	1,182	156	13%
2013 (**holdout sample**)	**1,216**	**100**	8%
Total	8,522	1,082	13%

Table 4. Estimated Coefficients (z-Statistics in Parentheses) from Logistics Regressions of 7306 firm-year observations from the period of 2004-2012

Independent variables	Training set	
Intercept	-8.68	(61.22)**
Incident history	2.33	(311.50)**
Firm age	0.02	(3.63)+
Revenue	0.23	(10.23)**
Total assets	0.17	(4.00)*
Industry-adjusted ROA	-0.83	(3.86)*
Percentage of government ownership	0.38	(4.93)*
Debt ratio	0.01	(0.01)
Financial leverage	0.00	(0.67)
Industry	(omitted)	
n (number of observations)	7,306	
-2 Log likelihood	4,604.70	
Cox & Snell R Square	14.71%	
Nagelkerke R Square	26.95%	

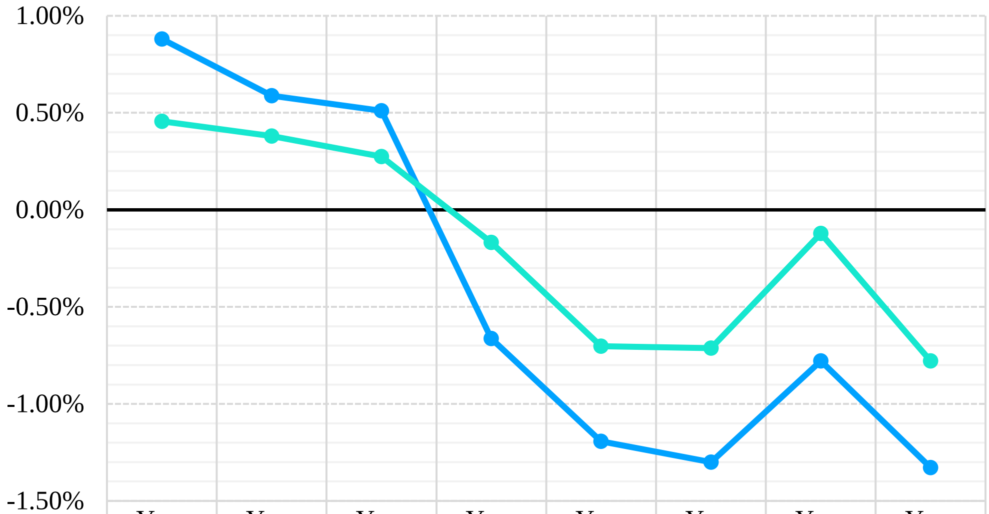
Note. All tests are two-tailed: $^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; Industry is categorical dummy variable of 26 industries, and we did not show it in the table to save space.

Table 5. Profile of firms with estimated probability of having violations in 2013 exceeds 0.5.

Industry category	Industry code	Industry	Number of firms with high estimated probability of having violations in 2013
Chemical products (C26-29, except C27)	C26	Raw Chemical Materials and Chemical Products	17
	C28	Chemical Fibre Manufacturing	4
	C29	Rubber and plastic product industry	1
	Sub-total		22
Metal and non-metallic mineral products (C30 - 33)	C30	Non-metallic Mineral Products	9
	C32	Smelting and Pressing of Nonferrous Metals	7
	C31	Smelting and Pressing of Ferrous Metals	4
	C33	Metal Products	2
	Sub-total		22
Others (all other not included)	C14	Food Manufacturing	4
	C15	Wine, drinks and refined tea manufacturing	4
	C13	Farm Products Processing	2
	C25	Petroleum Processing, Coking and Nuclear Fuel Processing	2
	Sub-total		12
Textiles and paper products (C17-18, C20, C22)	C22	Papermaking and Paper Products	7
	C17	Textile	2
	C18	Textiles, Garments and Apparel industry	1
	Sub-total		10
General equipment manufacturing (C34 - 41)	C36	Automobile Manufacturing	4
	C37	Railway, shipbuilding, aerospace and other transportation equipment manufacturing	3
	C34	General Equipment Manufacturing	1
	C39	Computer, communication and other electronical device manufacturing	1
	Sub-total		9
Pharmaceutical manufacturing (C27)	C27	Pharmaceutical manufacturing	7
	Sub-total		7
Total			82

Table 6. Firms to be selected for audit

Risk probability range	No. of firms	% (1)	Actual no. of firms with violations	% (2)	"returns on investment" ratio = (2) / (1)
0.9-1	13	1.07%	7	7%	6.55
0.8-1	23	1.89%	14	14%	7.40
0.7-1	38	3.13%	20	20%	6.40
0.6-1	59	4.85%	29	29%	5.98
0.5-1	82	6.74%	32	32%	4.75
0.4-1	112	9.21%	44	44%	4.78
0.3-1	169	13.90%	58	58%	4.17
0.2-1	262	21.55%	71	71%	3.30
0.1-1	584	48.03%	91	91%	1.89
0-1	1216	100.00%	100	100%	1.00



	Year -3 to 0	Year -2 to 0	Year -1 to 0	Year 0 to 1	Year 0 to 2	Year 0 to 3	Year 0 to 4	Year 0 to 5
Mean	0.88%	0.59%	0.51%	-0.66%	-1.19%	-1.30%	-0.78%	-1.33%
Median	0.46%	0.38%	0.28%	-0.17%	-0.70%	-0.71%	-0.12%	-0.78%

Figure 1. Mean and Median (Cumulative) Abnormal ROA Performance of Sample

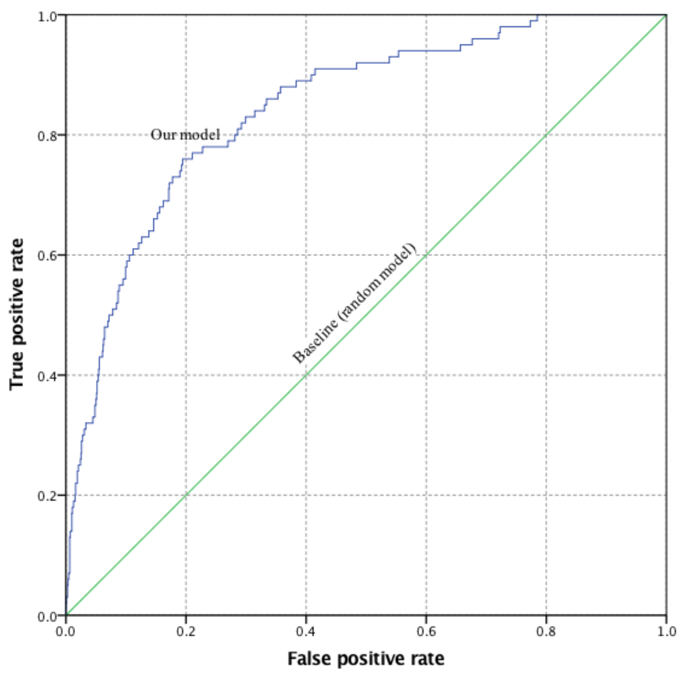


Figure 2. ROC curve of the prediction for our training-test model

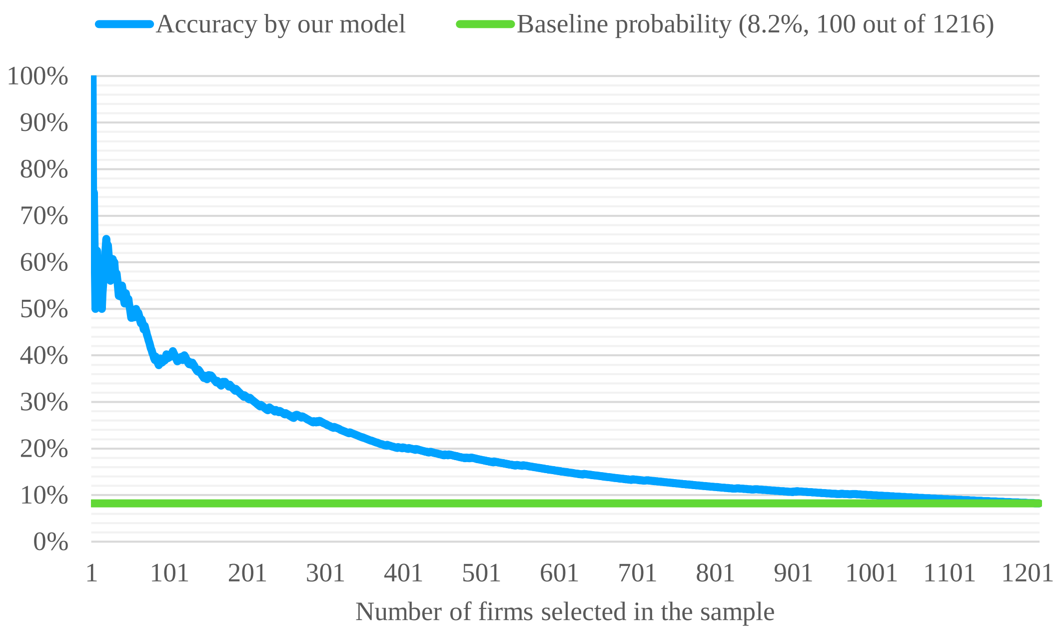


Figure 3. Predictive accuracy when selecting firms according to risk probability in descending order

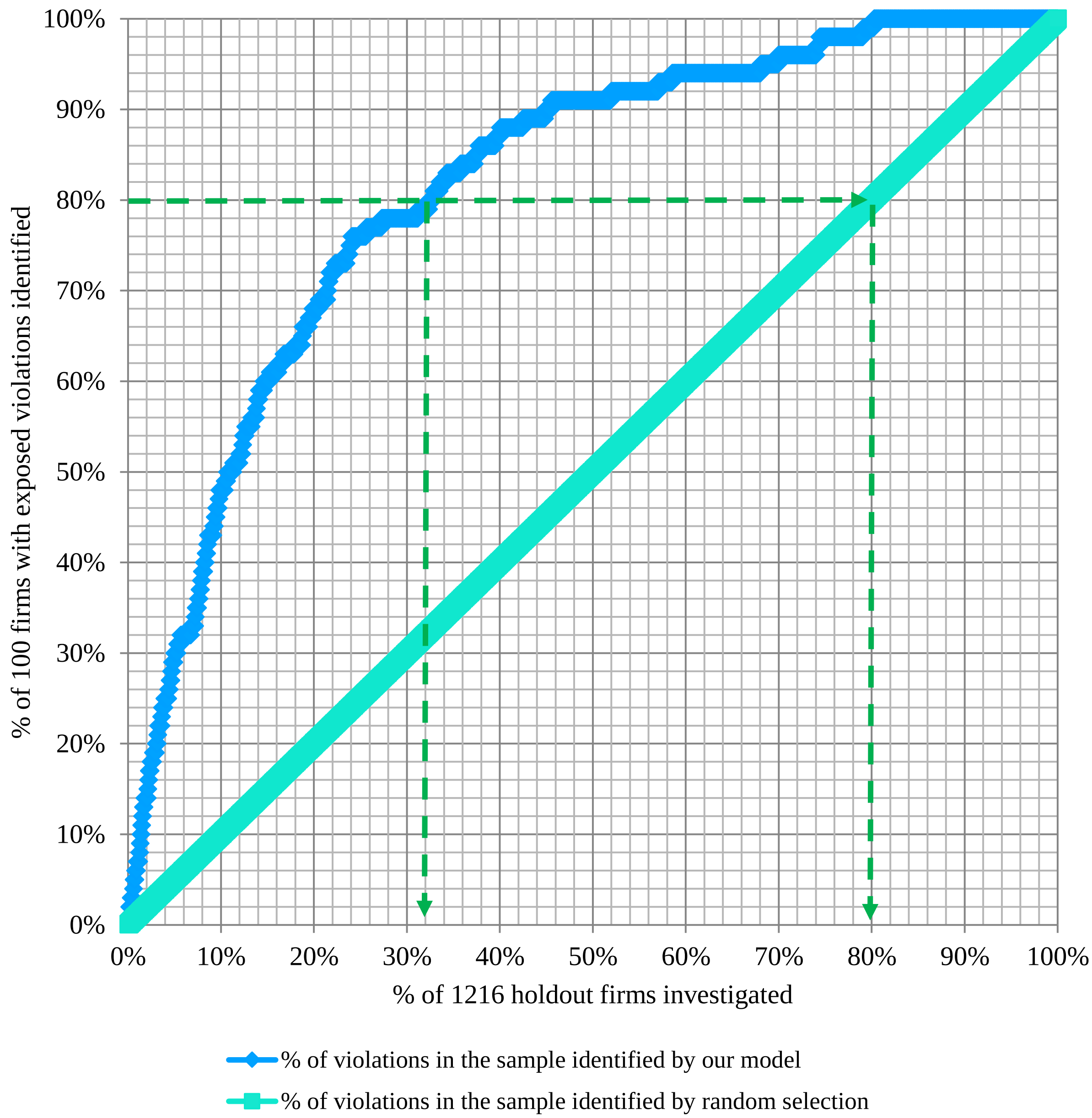


Figure 4. Returns on investment for firm audit selection strategy

Appendix A. Year-to-year abnormal ROA performance of sample firms

Table A1. Year-to-year abnormal ROA performance of sample firms

	Year -3 to -2	Year -2 to -1	Year -1 to 0	Year 0 to 1	Year 1 to 2	Year 2 to 3	Year 3 to 4	Year 4 to 5
n (number of observations)	719	721	721	721	719	716	638	541
Mean abnormal ROA	0.30%	0.08%	0.51%	-0.66%	-0.51%	-0.13%	0.74%	-0.47%
t -statistic	1.11	0.30	2.18^{*}	-2.53^{**}	-1.94^{*}	-0.52	2.78	-1.58^{+}
Median abnormal ROA	0.16%	0.00%	0.28%	-0.17%	-0.08%	-0.08%	0.37%	-0.16%
Wilcoxon signed-rank *Z*-statistic	1.36^{+}	0.27	1.75^{*}	-1.93^{*}	-1.82^{*}	-0.73	2.23	-1.68^{*}
% abnormal ROA (negative)	48.1%	49.9%	48.1%	52.1%	50.9%	51.4%	46.6%	51.8%
Binomial sign test *Z*-statistic	0.97	0.00	0.97	-1.12	-0.45	-0.71	1.70	-0.77

Note: $^{+}$ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$ (all tests are one-tailed).

Abnormal ROA performance "before" the event year during which violations were exposed

The first to third column of Table A1 present the year-to-year abnormal ROA of sample firms "**before**" the event year during which violations were exposed (i.e., from year -3 to year 0). We find that the mean (median) abnormal ROA of sample firms from year -1 to 0 are 0.51% (0.28%), and it is significantly larger than zero (both mean and median for $p < 0.05$). We also find that 48.1% of the abnormal ROA performance of the sample firms are negative (i.e., 51.9% of the samples have positive abnormal ROA), yet the figure is not statistically significant. We found that year -1 to 0 is the most significant period that the sample firms with exposed violation enjoyed a higher ROA performance over the matched control firms without exposed violations. We also find similar positive impacts on firms' abnormal ROA in the year -3 to year 2 and year -2 to year -1 period, but the effect is less significant compared to year -1 to 0, thus to avoid repetition, we omit the details. After all, the year-to-year abnormal ROA performance of sample is consistent with the findings from the cumulative abnormal ROA performance presented in Table 6.

Abnormal ROA performance "after" the event year during which violations were exposed

The fourth to eighth column of Table A1 present the year-to-year abnormal ROA performance "after" the event year during which violations were exposed. We find that the mean (median) abnormal ROA from year 0 to 1 is -0.66% (-0.17%) and significantly less than zero (with $p < 0.01$ for the mean, and $p < 0.05$ for the median). Also, we find that 52.1% of abnormal ROA performance associated with the sameple firms are negative, but they are not significantly greater than 50%. Observe the firth column (year 1 to 2) in Table A1, the results are largely the same as the fourth column (year 0 to year 1). These show that the fluctuation of abnormal ROA performance mainly happened around the event year.

On the seventh column (year 3 to 4), we unexpectedly record an increase in mean and median abnormal ROA period of the sample firms, but they are not significant. The negative trend of abnormal ROA continue in the year 4 to 5. We find that the mean (median) abnormal ROA of the sample firms are -0.47% (-0.16%) and it is significantly less than zero (with $p < 0.10$ for the mean, and $p < 0.05$ for the median). We also find that 51.8% of abnormal ROA are negative but not significantly greater than 50%. Figure A1 visualizes the mean and median abnormal ROA changes in each year-to-year period.

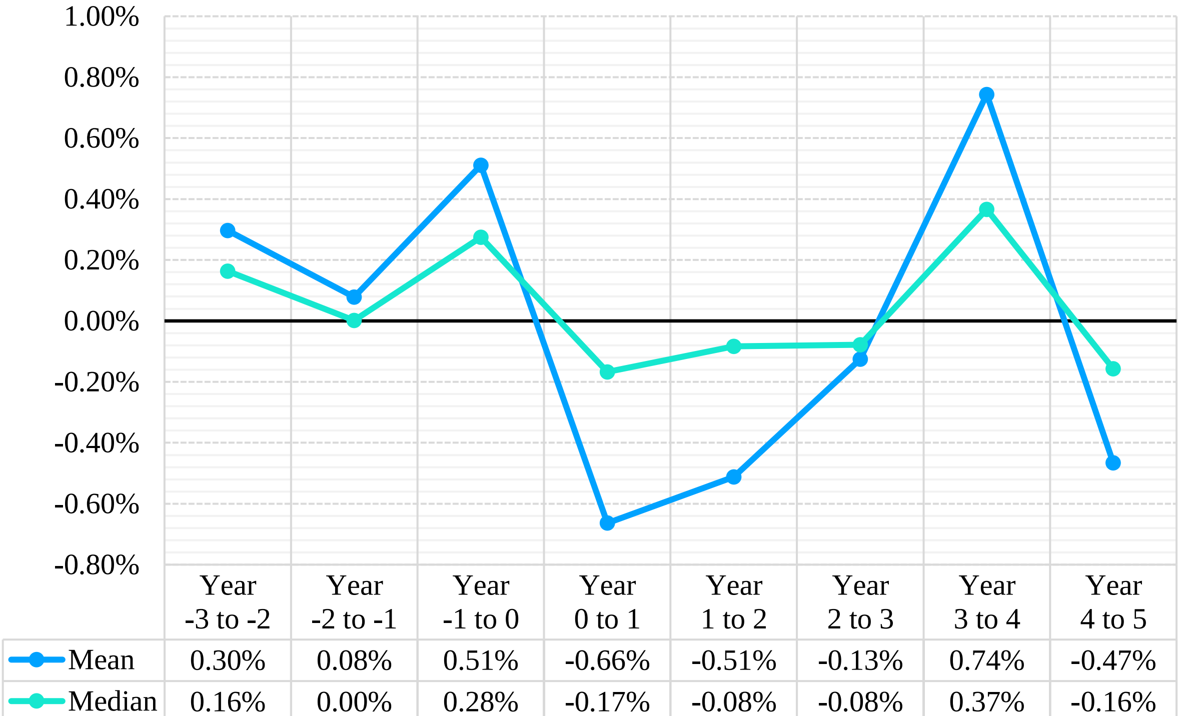


Figure A1. Mean and Median (Year-to-Year) Abnormal ROA Performance of Sample Firms.

Appendix B. An Expanded Logistics Regression Model.

Our expanded model includes: market-related factors such as debt-to-equity ratio, price-to-book ratio, gross margin, and market share. Adding these factors decreased sample size by 4.2% (304 observations) and did not improve the figures in model fit (i.e., -2 log likelihood, Cox & Snell R Square, Nagelkerke R Square) significantly. So, we did not include them in our model.

Table B1. Estimated Coefficients (z-Statistics in Parentheses) from Logistics Regressions of 7002 firm-year observations from the period of 2004-2012

Independent variables	Training set	
Intercept	-9.58	(52.83)**
Industry	-	
Incident history	2.34	(302.17)**
Firm age	0.02	(2.61)
Revenue	0.31	(13.08)**
Total assets	0.10	(1.17)
Industry-adjusted ROA	-1.22	(2.06)
Percentage of government ownership	0.36	(4.16)*
Debt ratio	0.07	(0.07)
Financial leverage	0.00	(0.62)
Price-to-book ratio	0.00	(0.06)
Debt-to-equity ratio	0.00	(0.06)
Gross Margin	-0.11	(0.06)
Market Share	-0.01	(0.12)
n	7,002	
-2 Log likelihood	4,414.36	
Cox & Snell R Square	15.09%	
Nagelkerke R Square	27.54%	

Note. All tests are two-tailed: $^{+}p < 0.10$; $*p < 0.05$; $**p < 0.01$; Industry is categorical dummy variable, and we did not show it in the table to save space.

Appendix C. Additional ROC curves.

Figure C1 depicts the ROC curve of the prediction for our training-test model that is based on 6124 firm-year observations from 2004 to 2011 as the training set to predict the remaining 2398 observations for the 2012-2013 period. Similarly, Figure C2 displays the ROC curve associated with 6855 random-select firm-year observations (80%) as the training set to predict the remaining 1667 observations (20%).

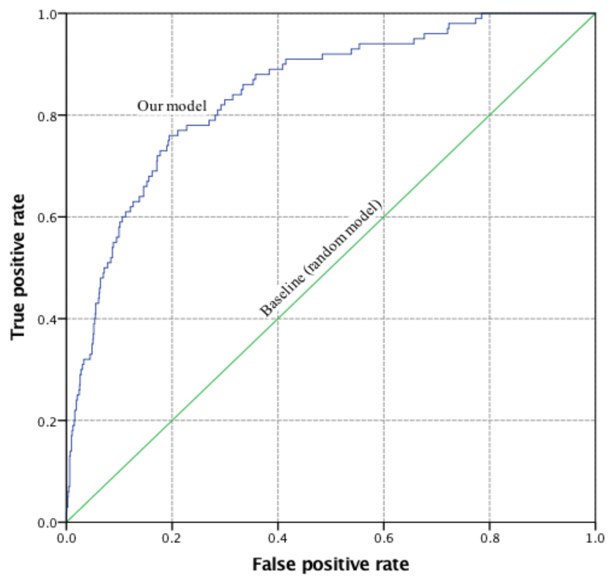


Figure C1. ROC curve of the prediction for our model, using 2004-2011 observations for training and 2012-2013 observations for test. The area under ROC curve is 0.853.

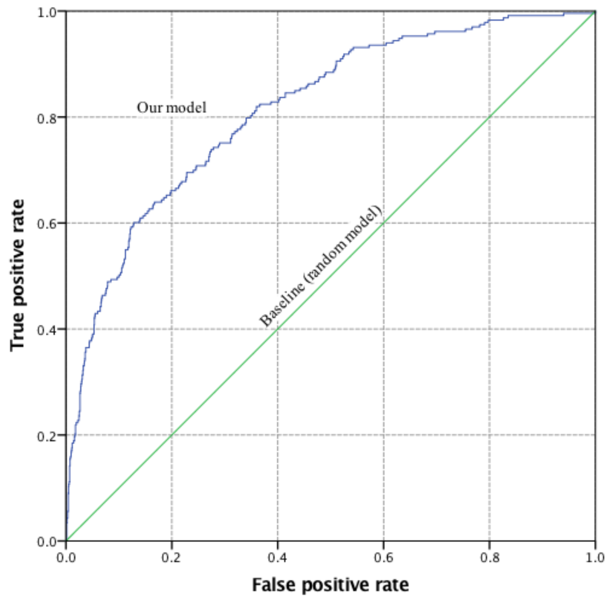


Figure C2. ROC curve of the prediction for our model, using random-select 80% of the data to predict the remaining 20%. The area under ROC curve is 0.815.