Dying to Survive: Unintended Consequences of Environmental Regulations on Industrial Accidents*

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Abstract

We investigate the impact of environmental regulations on industrial accidents by exploiting the 2014 revision of China's Environmental Protection Law (EPL), heralded as "the strictest environmental law in China's history." These tightened regulations may have significantly financially constrained pollution-intensive firms, forcing them to reduce precautionary spending on production safety in order to survive, thereby potentially increasing the risk of industrial accidents. With a difference-in-differences strategy, we compare changes in industrial accidents between pollution-intensive and non-pollution-intensive industries at the prefecture level before and after the implementation of the revised EPL. Our estimates indicate that stricter environmental regulations led to an approximately 60.4% increase in the number of industrial accidents in heavily polluting industries. Furthermore, we demonstrate that the reduction in firms' safety investments, caused by tighter financial constraints following the stricter regulations, is a plausible underlying mechanism. Our study highlights an additional hidden cost of environmental regulations that has been overlooked in the literature, suggesting that traditional estimates of the costs of environmental regulations may have significantly underestimated their broader societal impact.

Keywords: Environmental Regulations, Industrial Accidents, Safety Investments

JEL classification: Q58, J28, K32, Q52

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1 Introduction

Industrial accidents pose significant threats to global socioeconomic well-being (Boone et al., 2011; Cohn and Wardlaw, 2016; Tan et al., 2021; Charles et al., 2022). According to the International Labour Organization (2022), an estimated 2.78 million workers die annually due to industrial accidents, and an additional 374 million suffer from their impacts, resulting in an estimated 4% loss in global GDP.[1] In the U.S. alone, productivity and wage losses from industrial accidents totaled an estimated $44.8 billion in 2020 (Lavy et al., 2022). Severe industrial accidents—such as explosions or gas leaks—not only harm workers but also affect nearby residents, properties, and infrastructure, leading to widespread and devastating consequences (e.g., the Bhopal Disaster in India, 1984; Texas City Refinery Explosion in the United States, 2005).[2]

Undoubtedly, understanding the fundamental causes of industrial accidents is a critically important issue, yet one that remains relatively underexplored in the literature. We posit and empirically test the hypothesis that environmental regulations, while designed to improve environmental quality and enhance social welfare, may have inadvertently led to a significantly higher incidence of industrial accidents among pollution-intensive firms. While the multifaceted effects of environmental regulation have been well-documented in the literature (e.g., Jaffe et al., 1995; Greenstone, 2002; Chay and Greenstone, 2003; Greenstone et al., 2012; Ryan, 2012; Cai et al., 2016; Gibson, 2018; Chen et al., 2018; He et al., 2020; Liu et al., 2021; Sanders and Barreca, 2022; Cherniwchan and Najjar, 2022), this study fills a crucial gap regarding the unintended consequences of such regulations on industrial accidents. Additionally, our findings carry significant welfare and policy implications, as many of the most catastrophic industrial accidents occur in pollution-intensive firms, which are continually subject to environmental regulatory pressure.

This study argues that tightened environmental regulations could significantly financially constrain pollution-intensive firms, forcing them to reduce precautionary spending on production

[1]Further details on the impacts of work-related accidents can be found on the International Labour Organization's website: https://www.ilo.org/resource/news/nearly-3-million-people-die-work-related-accidents-and-diseases

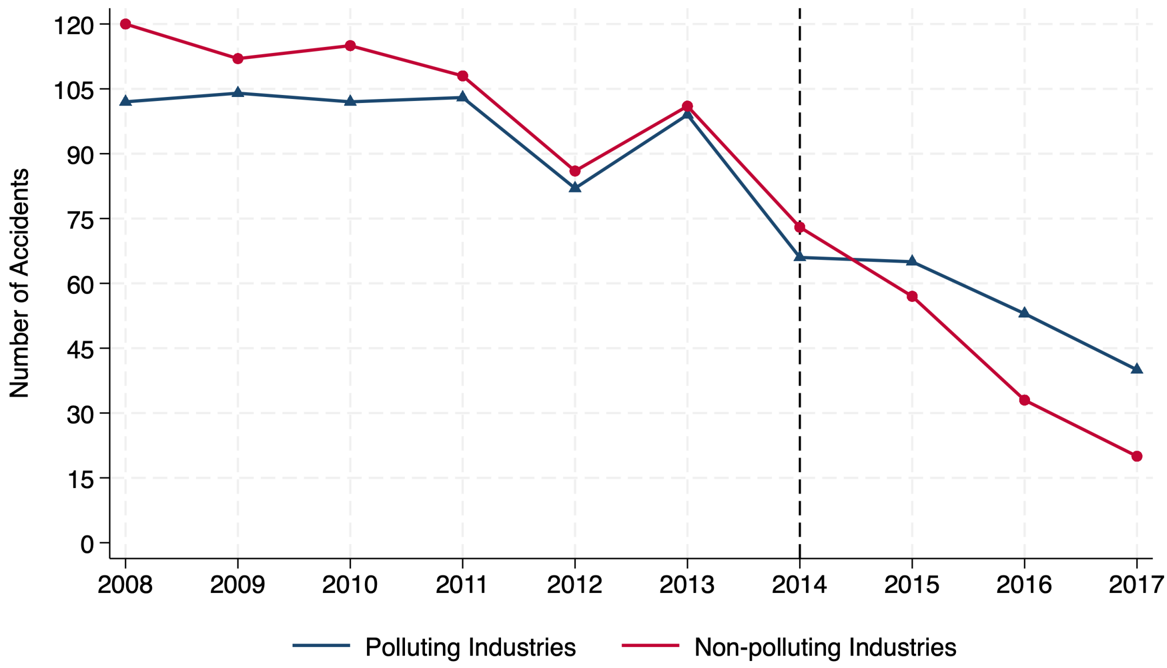
[2]Further details on the two catastrophic accidents can be found in the links below, respectively: https://www.britannica.com/event/Bhopal-disaster and https://www.csb.gov/bp-america-texas-city-refinery-explosion/

safety in order to survive, thereby potentially increasing the risk of industrial accidents. Specifically, with limited resources, firms may be compelled to prioritize meeting increasingly stringent pollution standards, which could lead to cuts to other expenses. Precautionary expenditures, such as safety investments, are not critical to a firm's short-term survival and are therefore the most likely to be reduced. Consequently, pollution-intensive firms may face a trade-off between environmental compliance and safety management. If this is the case, stringent environmental regulations could compromise safety, ultimately leading to a higher incidence of accidents in pollution-intensive industries.

China provides an ideal scenario for empirically studying this issue, given its unique combination of rapid industrialization and increasingly stringent environmental regulations. Over the past few decades, China's rapid economic growth, heavy reliance on fossil fuels, and insufficient environmental regulations have significantly deteriorated the country's environmental quality (World Bank, 2007). In response, the Chinese government substantially revised the Environmental Protection Law (EPL) in 2014, with the updated version coming into effect in January 2015. The 2014 revision of the EPL was heralded as "the strictest environmental law in China's history" (National People's Congress 2014). This revision significantly increased the penalties for firms exceeding pollution limits, placing greater pressure on them to allocate more resources toward pollution control. More importantly, the revision explicitly mandates that pollution control outcomes be included as a key evaluation criterion for local officials, while also imposing penalties on those involved in falsification or fraudulent activities. This motivated officials to take effective action against pollution. We observe a dramatic increase in the annual number of environmental penalties after 2014, and Greenstone et al. (2021) report a significant improvement in air quality in China following the same period. Both findings support the effective enforcement of the revised EPL.

It is noteworthy that the implementation of the revised EPL coincided with the occurrence of some of the most catastrophic industrial disasters in China, particularly in pollution-intensive industries. For instance, the Tianjin Explosion in 2015 caused 173 deaths, 798 non-fatal injuries,

Figure 1: Dynamics of Accidents in Polluting and Non-polluting Industries



Notes: This figure illustrates the dynamics of the number of accidents in polluting and non-polluting industries from 2008 to 2017. Polluting industries include both heavily and moderately polluting industries, while non-polluting industries consist of lightly polluting industries (including those with negligible pollution). The data on industrial accidents are sourced from WiseNews.

and an estimated economic loss of $9 billion. Similar disasters followed in subsequent years, such as the Fengcheng Power Station Collapse in 2016 (74 deaths, $15.48 million) and the Xiangshui Chemical Plant Explosion in 2019 (78 deaths, $284.3 million). In contrast, few industrial accidents of comparable magnitude in these industries were documented prior to 2014. Ample anecdotal evidence suggests that environmental regulations play a crucial role in triggering these tragedies. For instance, prior to the Xiangshui Chemical Plant explosion in 2019, the plant had been repeatedly penalized for non-compliance with environmental regulations, and prolonged exposure to increasing regulatory pressure may have ultimately led to the disaster.

Utilizing news data from the WiseNews database, we compile a panel dataset of industrial accidents at the prefecture level in China from 2008 to 2017. The advantage of news data is that it is recorded immediately after accidents, since it is not subject to later manipulation, which distinguishes it from official data sources (Ghanem and Zhang, 2014; Wallace, 2016; Fisman and Wang, 2015). Since environmental regulations primarily impact polluting industries, we categorize industrial accidents into those occurring in polluting industries and those in non-polluting industries, and present the annual trend for both categories. As shown in Figure 1, prior to 2014, the difference in the number of accidents between the two sectors is minimal. However, after 2014, when regulations were strengthened, the number of accidents in polluting industries became noticeably higher than that in non-polluting industries.

To identify the causal effect of environmental regulations on industrial accidents, we employ a difference-in-differences strategy. This method allows us to compare changes in industrial accidents between pollution-intensive and non-pollution-intensive industries at the prefecture level before and after the tightening of environmental regulations. Our estimation shows that strengthened environmental regulations led to an approximately 60.4% increase in the number of industrial accidents in pollution-intensive industries. To the best of our knowledge, this is the first empirical evidence suggesting that environmental regulations could exacerbate industrial accidents, leading to considerable welfare losses. Our identification strategy relies on the assumption that, in the absence of stricter environmental regulations, industrial accidents in pollution-intensive and non-pollution-intensive industries would have followed parallel trends. To validate this assumption, we employ an event study approach and find that the annual difference in accidents between pollution-intensive and non-pollution-intensive industries was minimal before 2014, only beginning to diverge afterward.

To further support our main conclusion, we conduct two triple-difference estimations. First, we leverage the variation in pollution intensity across industries and find that the increase in industrial accidents is particularly pronounced in heavily polluting industries compared to moderately polluting industries. Second, consistent with our hypothesis that the 47 "Key-Control Cities" designated by the central government could be more impacted by the tightened environmental regulations, we find a greater increase in accidents in pollution-intensive industries in these "Key-Control Cities" after 2014, compared to other cities. Additionally, we provide suggestive firm-level evidence to complement our prefecture-level analysis.

Next, we explore the mechanisms through which environmental regulations exacerbate industrial accidents among pollution-intensive firms. We provide evidence that a key mechanism is the reduction in safety investments. Safety investments are inherently vulnerable, and can be sacrificed when firms face tight financial constraints (Cohn and Wardlaw, 2016). Using panel data from China's publicly listed firms, we find that while the difference in safety expenditures between pollution-intensive and non-pollution-intensive firms was minimal prior to 2014, safety expenditures in pollution-intensive firms decreased significantly after the implementation of stricter environmental regulations, compared to their non-pollution-intensive counterparts. This evidence suggests that tighter financial constraints imposed by these regulations could have led to a decrease in firms' safety investments.

A potential concern regarding data quality is that some industrial accidents may not be reported by news outlets due to media censorship. We address this concern in several ways. First, we argue that our results remain unbiased as long as the omission of reports does not selectively target accidents in pollution-intensive industries over non-pollution-related ones. Second, recognizing the possibility of selection bias based on accident severity-whereby minor accidents may be deliberately omitted by news reporters, while only those too significant to conceal are reported-we conduct an analysis restricted to accidents resulting in no more than three fatalities (officially classified as 'Ordinary Accidents' in China) and find similar results. Finally, we merge our dataset with the official accident dataset and re-estimate our model. While the official dataset has inherent flaws, it serves as a valuable complement for validating the robustness of our findings. As expected, we observe consistent results in the consolidated dataset. Overall, we provide substantial evidence that our results are robust.

Although Figure 1 shows a decline in the number of reported industrial accidents after 2013 under increasingly strict censorship, the actual number of such accidents in China may have been rising rather than falling during this period. First, there was a significant increase in major accidents after 2013, which were more difficult to conceal. Table A.2 presents all major industrial accidents in

China that resulted in more than 60 deaths between 2008 and 2017. Notably, all of these accidents occurred after 2013. Second, in response to the surge in major accidents, the Chinese government ceased publicly releasing information on industrial accidents from 2018 onward, suggesting a concern that disclosing such information could threaten social stability.[3] Finally, even after 2018, the government continued to issue numerous laws and regulations addressing production safety, with national leaders consistently emphasizing its critical importance in various contexts, further indicating the persistent severity of China's production safety issues. Therefore, this study is set against the backdrop of a worsening production safety problem in China, where increasingly stringent environmental regulations may serve as a deeper underlying cause of the deteriorating conditions.

Our paper makes three contributions to the literature. First, we contribute to the research on the unintended consequences of environmental regulations (e.g., Jaffe et al., 1995; Greenstone, 2002; Chay and Greenstone, 2003; Greenstone et al., 2012; Ryan, 2012; Cai et al., 2016; Gibson, 2018; Chen et al., 2018; He et al., 2020; Liu et al., 2021; Sanders and Barreca, 2022; Cherniwchan and Najjar, 2022).[4] The purpose of environmental regulations is to reduce environmental pollution, thereby improving social welfare. However, in practice, these regulations can result in economic costs or other unexpected costs. We contribute to this strand of literature by providing, to the best of our knowledge, the first empirical evidence of the detrimental effects of environmental regulations on industrial accidents and the associated potential welfare losses.

Second, we contribute to the literature on the determinants of industrial accidents or workplace safety. The literature has established that numerous factors can affect industrial accidents, such as political factors (Nie et al., 2013; Fisman and Wang, 2015; Jia and Nie, 2017; Shi and Xi, 2018) and economic factors (Rose, 1990; Boone et al., 2011; Asfaw et al., 2013; Cohn and Wardlaw, 2016; Tan

[3]A similar situation occurred recently in 2023, when, amidst an economic downturn and historically high youth unemployment rates, the National Bureau of Statistics announced it would stop publishing youth unemployment statistics due to "technical issues."

[4]There is also an extensive body of literature demonstrating the positive or neutral effects of environmental regulations (e.g., Berman and Bui, 2001; Snyder et al., 2003; List et al., 2003; Greenstone and Hanna, 2014; Tanaka, 2015; Shapiro and Walker, 2018; Wang et al., 2018; Duan et al., 2021; Bo, 2021; Xie and Yuan, 2023).

et al., 2021; Charles et al., 2022). Our study takes a broader perspective on this issue, highlighting that distorted incentives for reducing precautionary expenditures among firms facing increasingly stringent pollution standards are a key factor contributing to the rise in industrial accidents. In their efforts to survive, these firms are compelled to cut back on precautionary spending, neglecting the substantial societal costs. As a result, safety investments fall far below the socially optimal level, exacerbating the risks of industrial accidents.

Third, more broadly, we contribute new evidence to the longstanding debate comparing market failures and government failures (e.g., Stiglitz, 1989; Krueger, 1990; Datta-Chaudhuri, 1990; Shleifer and Vishny, 1998; Acemoglu and Verdier, 2000; Glaeser and Shleifer, 2003; Winston, 2007; Stiglitz, 2010; Morantz and Kessler, 2010; Li et al., 2011; Furton and Martin, 2019). Environmental regulations are implemented in many countries to address the typical market failure of pollution, with the goal of enhancing social welfare. However, due to information gaps or capacity constraints, these regulations can sometimes result in unintended adverse outcomes, potentially leading to government failures. While it remains challenging to assess whether government failures outweigh market failures, our paper highlights a previously overlooked negative consequence of environmental regulations. This finding should be considered in future regulatory designs to better address market failures while minimizing the risk of government failures.

The rest of the paper is organized as follows. In section 2, we illustrate the background of environmental regulations and industrial accidents in China. Section 3 introduces data sources. Section 4 introduces our empirical strategy. Section 5 presents empirical results. Section 6 discusses potential mechanisms. Section 7 concludes the paper.

2 Background

2.1 The Environmental Protection Law in 2014

As the world's largest industrial producer and pollution emitter, China has long grappled with a challenging trade-off between economic development and environmental protection (Liu et al., 2021). Since the 1980s, heavy reliance on fossil fuels and the rapid growth of manufacturing industries have been major contributors to environmental degradation in China. Air quality remained poor throughout the early 2010s, with severe air pollution episodes in major cities like Beijing during this period sparking widespread public outcry over the lack of transparency regarding pollution levels and the absence of effective government responses (Barwick et al., 2024). Despite the environmental standards set by the central government, local governments paid limited attention to addressing pollution, as their strong incentives to pursue economic growth often conflicted fundamentally with the goals of environmental protection (Jia, 2024).

In response to the severe pollution issue and growing public dissatisfaction, the central government launched a series of regulatory policies in the early 2010s to combat pollution. Notable initiatives included the "Twelfth Five-Year Plan for Air Pollution Prevention in Key Areas" in 2012 and the "Action Plan for Air Pollution Prevention and Control" (commonly known as "Air Ten") in 2013. The Environmental Protection Law (EPL) formalized China's system of environmental regulations (Karplus et al., 2021). Originally established in 1989, the EPL underwent a significant revision in 2014, with the updated version coming into effect in January 2015. The number of legal provisions was increased from 47 to 70, significantly enhancing the law's enforceability and practicality. This revision granted greater enforcement power to environmental agencies. More importantly, it strengthened governmental accountability by explicitly stipulating that pollution control outcomes would be included as one of the evaluation criteria for local officials, thereby motivating them to take more effective actions against pollution.

The 2014 revision of the EPL was heralded as "the strictest environmental law in China's history" (National People's Congress 2014). There are several reasons for this statement. First, the revised EPL removed the previous cap of 1 million RMB on fines for environmental violations, effectively eliminating any financial limit on penalties for severe pollution offenses. Second, it replaced the "monthly penalty" system with a "daily penalty" system, ensuring that firms violating pollution standards would incur fines every day until they achieved compliance.[5] In 2016, these daily fines

[5]For example, if the environmental protection department has decided to impose an administrative fine of 100,000 RMB on the company for illegal pollution activities and has ordered the company to rectify the issue within a specified time frame. However, if the company refuses to rectify within the specified period, the environmental protection

amounted to over 800 million RMB.[6] Third, the revised EPL introduced regulatory measures, such as the suspension of production and confiscation, to facilitate effective remediation. Fourth, as an administrative law, the revised EPL stipulated administrative detention as a punitive measure, a provision rarely seen in prior environmental regulations or laws in China. This administrative detention applies not only to serious environmental violations but also to environmental monitoring agencies and government officials involved in falsification or fraudulent behavior. This punitive measure directly targets the protective forces behind polluting firms, aiming to fully resolve the persistent issue of recurring pollution violations. In sum, the 2014 revision of the EPL significantly increases the costs for pollution-intensive firms to violate regulations, not only through financial penalties but also by introducing the potential risks of suspension and even administrative detention.

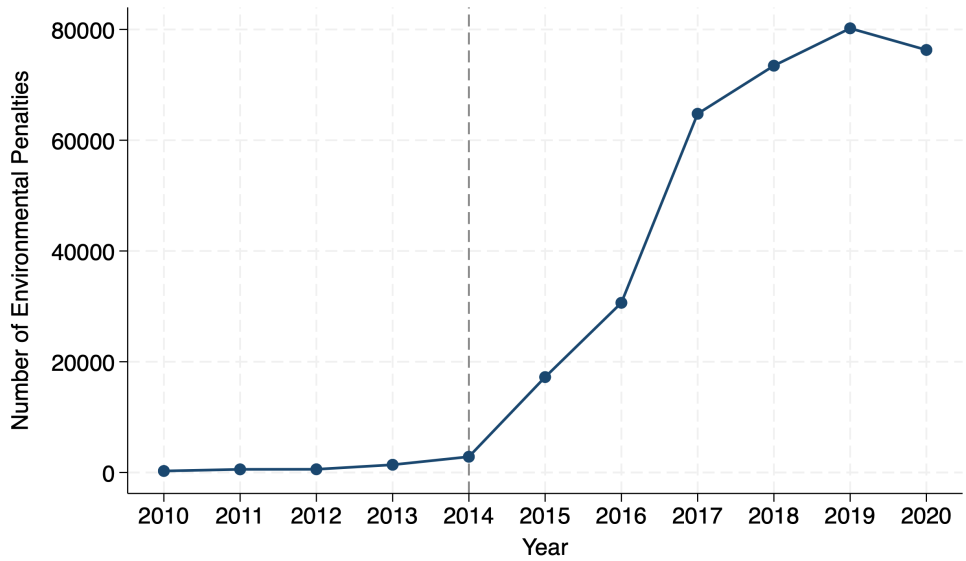
Real-world evidence indicates that the revised EPL was effectively enforced, as it granted greater enforcement power to environmental agencies. Data from PKU Law shows that the annual number of environmental penalties surged significantly after 2014, as shown in Figure 2.[7] This increased enforcement efforts corresponded with notable improvements in air quality across China. Greenstone et al. (2021) found a marked improvement in air quality after 2014, demonstrated by a sharp decline in major air pollutants, including $PM_{2.5}$, PM_{10}, SO_2, and CO. Figure 3 illustrates the trend in the average concentration of Aerosol Optical Depth (AOD)-a widely used measure of atmospheric particulate pollution obtained through remote sensing-over recent years. The data reveal a clear decline in AOD after 2014, underscoring the effectiveness of these stringent regulatory policies.

department may impose a fine of 200,000 RMB starting from the day after the correction order was issued. On the third day, the fine will increase to 300,000 RMB, and the department may continue to impose additional fines on a daily basis.

[6] See the report: http://www.xinhuanet.com/politics/2017-04/19/c_1120836039.htm

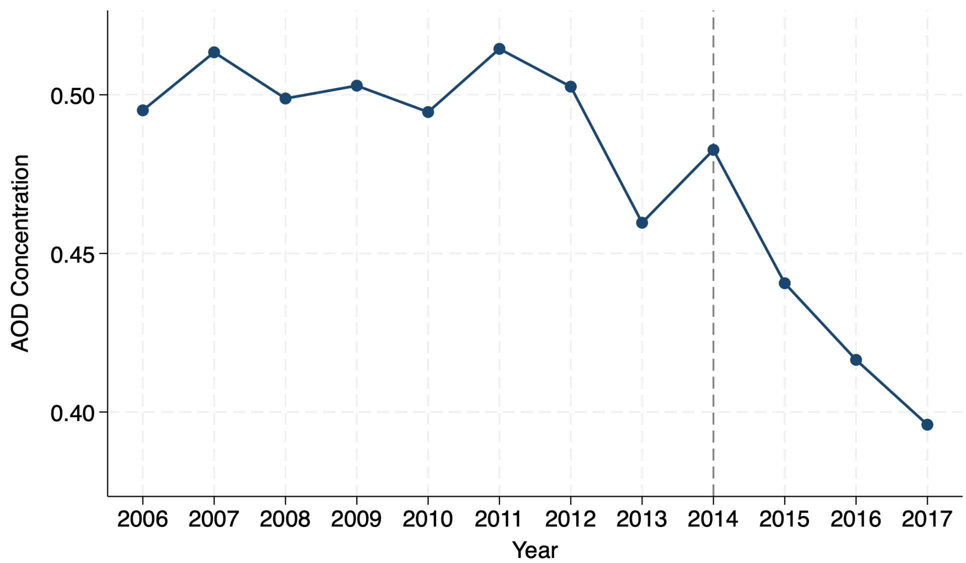
[7] PKU Law contains a comprehensive record of historical laws and regulations from both the Chinese government and the Communist Party of China, with records dating back to the CCP's establishment in 1921. Its case database includes hundreds of millions of civil, criminal, and administrative legal cases that are otherwise difficult to reliably access online.

Figure 2: Annual Number of Environmental Penalties in China



Notes: This figure illustrates the annual number of environmental penalties in China. Data is sourced from PKU Law.

Figure 3: AOD Concentration in China



Notes: This figure illustrates the dynamics of Aerosol Optical Depth (AOD) concentration from 2006 to 2017. Data is sourced from Barwick et al. (2024).

2.2 Industrial Accidents in China

Despite remarkable growth in manufacturing industries since the economic reform, industrial safety in China remains disproportionately vulnerable. Industrial disasters with catastrophic consequences have frequently occurred in China. The worker death rate in China is more than 20 times higher than that of the U.K. (Fisman and Wang, 2015). According to the State Administration of Work Safety (SAWS), more than 83,000 deaths occurred in workplace accidents in 2009, equating to approximately one in every 10,000 workers (China Safe Production Yearbook 2009). Between 2005 and 2022, 19 workplace accidents were recorded, each resulting in more than 60 fatalities. Many of these catastrophic accidents occurred in pollution-intensive industries and took place after 2014. For instance, the Tianjin Explosion in 2015 caused 173 deaths, 798 non-fatal injuries, and an estimated economic loss of $9 billion; the Fengcheng Power Station Collapse in 2016 resulted in 74 deaths and an estimated loss of $15.48 million; and the Xiangshui Chemical Plant Explosion in 2019 led to 78 deaths and an estimated loss of $284.3 million.

Several factors may have contributed to the frequent occurrence of industrial disasters in China. First, official reports following such accidents often cite outdated equipment, insufficient employee training, and disorganized workplace management as key contributing factors. These issues reflect inadequate investments in workplace safety, as firms commonly cut costs by underinvesting in this area.

Second, corruption and collusion play a significant role in these industrial disasters. Fisman and Wang (2015) argue that bribery often undermines safety compliance, and political connections are frequently used to bypass regulations. This partially explains the persistence of poor working conditions. Jia and Nie (2017) provide further evidence of collusion between regulators and firms, which negatively impacts workplace safety. With protection from local governments, firms may avoid making the necessary investments to improve safety standards.

Third, the issue often stems from weak enforcement rather than the absence of adequate laws and regulations. The government consistently emphasizes the importance of workplace safety with slogans like “workplace safety is paramount” and “hold fast to the bottom line of workplace safety.” It has also taken measures, such as establishing the State Administration of Work Safety (SAWS), to address these concerns. However, despite numerous regulations and the significant authority granted to SAWS, enforcement remains insufficient, and industrial disasters continue to occur. The root cause lies in the inadequacy of incentive mechanisms. Specifically, since firms are the decision-makers regarding production safety, if the relevant regulations fail to effectively incentivize them to make adequate safety investments, then ensuring such safety would remain merely empty words.

2.3 Environmental Regulations, Firms’ Responses, and Industrial Accidents

Firms’ responses to environmental regulations have significant economic implications (Greenstone, 2002; He et al., 2020; Liu et al., 2021). Existing literature has primarily focused on three corresponding strategies: reducing production scale, upgrading for cleaner devices, and relocating plants to regions with less stringent regulations (Karplus et al., 2021), each of which involves considerable economic costs. Yet, these strategies may be unaffordable or undesirable to many firms that are already struggling to survive on slim profit margins, even without regulation. To survive in the market, such firms may opt to cut investments in other areas to meet the environmental standards. This reallocation of resources is preferable to firms as long as the potential benefits of regulatory compliance outweigh the losses incurred from reducing other investments.

Similar to other investments like R&D, firms finance safety investments through either internal cash flows or external credit. The costs of safety investments include the purchase of tangible assets, such as safety equipment, as well as expenditures on intangible assets like employee training, monitoring, enforcing safety compliance, and fostering a safety-oriented culture within the firm. Compared to other investments, the returns on safety investments are often vague and relatively low in the short run, making them easy to sacrifice when firms face tight financial constraints (Filer and Golbe, 2003; Cohn and Wardlaw, 2016).

In practice, given their limited resources, regulated firms may struggle to balance environmental compliance with safety management. As pressure from environmental regulations intensifies, firms may be compelled to allocate more resources toward pollution control, which can lead to reduced spending on safety investments. Insufficient safety investments inevitably increase production hazards. Consequently, strict environmental regulations could inadvertently lead to more industrial accidents.

This issue is particularly relevant in developing countries such as China and India, where industrial safety is already fragile, and substandard workplace conditions are common, even in the absence of regulation (Fisman and Wang, 2015). Given the existing inadequacies in production safety, any further reduction in safety investments could have severe consequences. In such contexts, environmental regulations could have an even more pronounced impact, potentially exacerbating the occurrence of industrial disasters, particularly in pollution-intensive industries that are more heavily exposed to these regulations.

Anecdotal evidence from China also suggests that environmental regulations may have played a role in catalyzing industrial disasters. For example, before the explosion in 2019, the Tianjiayi Chemical Plant in Xiangshui was penalized ten times for non-compliance with environmental regulations, with accumulated fines totaling at least 1.6 million RMB. Facing significant pressure from these regulations, the firm was compelled to prioritize regulatory compliance over production safety. Consequently, in February 2018, the Office of SAWS reported several safety-related issues at the company: special operations workers had not passed the required assessments, production facilities were incomplete, and control cabinets and monitoring rooms were improperly set up. Additionally, in April 2018, the firm's pollution problems were exposed on CCTV, China's official media platform, leading to a four-month shutdown. This incident imposed unprecedented environmental regulatory pressure on the company. Merely six months after resuming operations, the plant suffered a catastrophic explosion, resulting in 78 deaths and more than 640 injuries. A similar incident occurred at the Panjinhaoye Chemical Firm in Liaoning, which faced substantial penalties for partial compliance with environmental regulations before an explosion resulted in 13 fatalities. These cases suggest that prolonged exposure to extreme regulatory pressure may have ultimately contributed to these disasters.

3 Data

3.1 Data Sources

Utilizing news data from WiseNews database, we compile a panel dataset of industrial accidents at the prefecture level in China from 2008 to 2017. WiseNews includes over a hundred news media outlets in Mainland China, Hong Kong, and Taiwan, covering national, provincial, and prefecture-level newspapers (Qin et al., 2018). We collect data on industrial accidents by searching for news reports containing the Chinese keywords for "accidents" and "deaths." For each recorded accident, we gather two key pieces of information: the year and the prefecture-level city of the accident, as well as the industry involved, which can be identified from the titles and highlights of the news reports.

Our sample ends in 2017 due to increasingly strict media censorship of newspaper reports on industrial accidents. Since 2013, the Chinese government has significantly strengthened media censorship. That year, it issued the "Notice on the Legal Punishment of Online Rumor Crimes," intensifying internet censorship. At the February 2014 meeting of the Central Leading Group for Cybersecurity and Informatization, national leaders emphasized the Party's critical role in guiding public opinion. Following this, the government allocated more resources to steer the "correct" orientation of public discourse (King et al., 2017). A series of laws and regulations were subsequently enacted to reinforce media censorship and steer public discussion. Therefore, the decline in news reports of accidents after 2013 occurred within this broader context, reflecting enhanced control over negative news coverage through stricter media censorship. Since 2018, the State Administration of Work Safety (SAWS) has ceased releasing information on industrial accidents, coinciding with more stringent restrictions on reporting such accidents. Consequently, news reports on these accidents have almost disappeared thereafter.

We take several steps to clean the raw dataset. First, we omit the news unrelated to industrial accidents, such as those covering natural disasters, traffic accidents, and safety education or propaganda. Second, we exclude the news about accidents in the coal mining industry. Beginning in the 2000s, the central government intensified regulation of this sector. Specifically, coal mining accidents were placed directly under the monitoring and regulation of SAWS, distinguishing them from other types of workplace accidents. Over the subsequent decade, workplace safety in the coal mining industry saw a marked improvement, with annual fatalities dropping from a peak of 7,016 in 1994 to 228 in 2020. Therefore, including coal mining accidents could confound our analysis. Third, we eliminate duplicate reports of the same accident, as the same incident may be covered by multiple news outlets. This approach ensures that each news report in our data represents a unique industrial accident.

Based on the comprehensive pollution emission intensity calculated by Jie and Bin (2014), industries are classified into heavily polluting, moderately polluting, and lightly polluting categories. The list of heavily polluting industries and moderately polluting industries is displayed in Table A.3. All industries that are neither classified as heavily polluting nor moderately polluting are categorized as lightly polluting industries, including those with negligible or minimal pollution. Following this classification, we categorize industrial accidents by the type of industry they occur in. Subsequently, we aggregate the number of industrial accidents for each industry type at the prefecture level. In general, polluting industries refer to both heavily and moderately polluting industries, while non-polluting industries refer to lightly polluting industries. However, since heavily polluting industries are most significantly impacted by environmental regulations, we define them as pollution-intensive industries and use them as our treatment group. In our baseline estimation, we test the robustness of our results by also presenting findings where both heavily and moderately polluting industries are classified as the treatment group. This broader classification helps assess whether the effects observed in heavily polluting industries also extend to moderately polluting sectors.

We also categorize the prefecture-level cities into "Key-control Cities" and others based on the official document "Twelfth Five-Year Plan for Air Pollution Prevention in Key Areas" announced by the central government in 2012. The document identified 47 cities as "Key-control Cities," where regulations were to be implemented more strictly than in other areas. These cities include regions such as the Jing-Jin-Ji Metropolitan Region, the Yangtze River Delta Economic Zone, and the Pearl River Delta Metropolitan Region. Although our sample period ends in 2017, the list remained unchanged until 2018, when the "Three-Year Action Plan to Win the Blue Sky Defense War" expanded it to include 80 cities.

In additional to the data from WiseNews, we also use various other databases in our analysis. To validate robustness, we supplement our data on industrial accidents with official accident reports from SAWS for the period 2008–2017. While official records are undeniably prone to manipulation (Ghanem and Zhang, 2014; Wallace, 2016; Fisman and Wang, 2015), they can still serve as a useful complement to our dataset as a robustness check. We also gathered information on firms involved in industrial accidents from Tianyancha to provide further evidence.[8] Additionally, we employ firm-level data from The China Stock Market and Accounting Research (CSMAR) and Annual Survey of Industrial Firms (ASIF) to shed light on the underlying mechanism. CSMAR provides detailed and high-quality data on publicly listed firms in China's stock markets. The database includes a wide range of information, such as financial statements, ownership structures, and industry classifications. The Annual Survey of Industrial Firms (ASIF) is a large-scale, firm-level dataset collected and maintained by China's National Bureau of Statistics (NBS). It covers a comprehensive sample of industrial firms with annual revenue exceeding 5 million RMB, making it one of the most extensive data sources for studying China's manufacturing and industrial sectors.

3.2 Description of Statistics

Table 1 presents the summary statistics of the data we use. Panel A of Table 1 shows that, on average, a prefecture-level city experienced 0.568 accidents annually during the period 2008–2017. Of these, 0.212 occurred in heavily polluting industries, 0.070 in moderately polluting industries, and 0.286 in lightly polluting industries. Although the average annual number of accidents in heavily polluting industries is lower than that in lightly polluting industries (0.212 vs. 0.286), the most severe industrial accidents in heavily polluting industries caused up to 168 fatalities, compared

[8] Tianyancha (https://www.tianyancha.com/) is a search platform containing public information on all Chinese registered firms.

to a maximum of 35 fatalities in the most severe accidents within lightly polluting industries. This suggests that accidents in pollution-intensive industries are significantly more life-threatening and may also have far-reaching and more severe impacts on social welfare.

Panel B of Table 1 presents data from CSMAR, which provides detailed information on publicly listed firms from 2008 to 2017. We use special reserves allocated for safety production costs as a proxy for safety expenditures. Panel C presents the summary statistics of firm-level data from the Annual Survey of Industrial Firms. Notably, we use expenditure on training employees as a plausible proxy for safety investments. Additionally, we include insurance investments as a type of precautionary expenditure.

We then present the trend of annual industrial accidents in polluting and non-polluting industries in Figure 1. As shown, prior to the 2014 revision of environmental regulations, the difference in annual industrial accidents between polluting and non-polluting industries was relatively small. However, after 2014, the annual number of industrial accidents occurring in polluting industries became noticeably higher than in non-polluting industries. The figure supports the parallel-trends assumption and reveals a divergent trend in accidents between polluting and non-polluting industries following the enforcement of stringent environmental regulations.

Table 1: Summary Statistics

	(1) Obs	(2) Mean	(3) SD	(4) Min	(5) Max
	Panel A: WiseNews Accidents				
Industrial Accidents	5,760	0.285	0.680	0	10
Industrial Accidents (heavily polluting industries)	2,880	0.212	0.549	0	6
Industrial Accidents (moderately polluting industries)	2,880	0.070	0.314	0	5
Industrial Accidents (lightly polluting industries)	2,880	0.286	0.745	0	10
Fatalities	5,760	0.894	3.938	0	168
Fatalities (heavily polluting industries)	2,880	0.759	4.344	0	168
Fatalities (moderately polluting industries)	2,880	0.240	2.555	0	124
Fatalities (lightly polluting industries)	2,880	0.789	2.443	0	35
	Panel B: CSMAR				
ln (Safety Expenditures)	11,199	2.917	4.279	0	16.408
ln (Assets)	11,199	15.011	1.397	9.029	21.601
	Panel C: ASIF				
ln (Training Expenditures)	1,081,017	1.289	1.792	0	12.402
ln (Insurance Expenditures)	2,084,835	1.285	1.884	0	12.714
ln (Profits)	2,084,835	3.657	5.494	-15.747	18.595
ln (Assets)	2,084,565	9.633	1.736	0	20.152

Notes: Panel A presents data sourced from WiseNews, showing the number of accidents and fatalities, and these statistics categorized by industry type. Panel B presents data from CSMAR. Panel C presents data from the Annual Survey of Industrial Firms (ASIF) during the period 2000–2007. The logs of safety expenditures, assets, training expenditures and insurance expenditures are calculated by transforming the initial variable X with $L(X) = ln(1 + X)$. Since profits can take negative values, the log of profits is calculated following John and Draper (1980).

4 Empirical Strategy

4.1 Difference-in-Differences

To identify the causal impact of tightened environmental regulations on industrial accidents, we employ a difference-in-differences model. Specifically, we examine whether industrial accidents became more likely to occur in pollution-intensive industries compared to non-pollution-intensive industries after 2014, the year when environmental regulations were strengthened in China. To test this, we estimate the following equation:

$$Accident_{cit} = \beta Post2014_t \times Pollution_i + \alpha_{ci} + \alpha_{ct} + \epsilon_{cit}, \quad (1)$$

where c and t represent prefecture-level city and year, respectively; i represents the industry type, differentiating between pollution-intensive industries and non-pollution-intensive industries. $Accident_{cit}$ measures the aggregate number of industrial accidents of type i that occurred in city c during year t. $Post2014_t$ is a dummy variable that equals 1 for years after 2014, and 0 otherwise. $Pollution_i$ is a dummy variable equal to 1 for pollution-intensive industries, and 0 otherwise. Heavily polluting industries are classified as pollution-intensive industries. In our baseline estimation, we also present results where both heavily and moderately polluting industries are grouped under the category of pollution-intensive industries. We control for city-by-industry type fixed effects (α_{ci}) to account for the time-invariant characteristics at the city-industry type level that could affect industrial accidents, such as the infrastructure quality by industry and historical industrial practices. Notably, the stand-alone coefficient on $Pollution_i$ is absorbed by the city-by-industry type fixed effects. Time-varying city-level characteristics, such as the scale of the city's economy, may influence industrial accidents. In our preferred specification, we control for city-by-year fixed effects (α_{ct}) to account for all potential impacts of time-varying prefecture-level characteristics on industrial accidents. These fixed effects are very restrictive. Standard errors are clustered at the city level.

The coefficient of interest is β, which captures the causal effect of strengthened environmental regulations on accidents in pollution-intensive industries. A significantly positive β suggests that industrial accidents occur more frequently in pollution-intensive industries compared to non-pollution-intensive industries following the implementation of strengthened regulations. Intuitively, if the tightened regulations exacerbate workplace safety issues in pollution-intensive industries, we would observe a relative increase in accidents in these industries compared to non-pollution-intensive industries after 2014.

4.2 Event Study

Our identification assumption for the difference-in-differences estimation is that, in the absence of strengthened regulations, industrial accidents of pollution-intensive and non-pollution-intensive industries would have evolved along parallel trends. As shown in Figure 1, the annual number of industrial accidents in polluting industries and that in non-polluting industries were minimal before 2014. To further validate the parallel trends assumption, we employ an event study approach. Specifically, we estimate the following equation, which allows us to capture the dynamics of industrial accidents before and after the implementation of stricter environmental regulations.

$$Accident_{cit} = \sum_{k=-6}^{k=-1} \mu_k \times Pollution_i + \sum_{k=1}^{k=3} \mu_k \times Pollution_i + \alpha_{ci} + \alpha_{ct} + \epsilon_{cit}, \tag{2}$$

where c, t and i represents prefecture-level city, year, and industry type, respectively; μ_k captures the relative event-time indicators. That is, μ_k is an indicator variable that takes the value 1 if it is k years relative to 2014, the year when environmental regulations were strengthened. As is typical in the event study frameworks, we make the normalization $\mu_0 = 0$, so that all coefficients represent differences in accidents relative to the year 2014. The fixed effects are the same as those in Equation 1, and standard errors are clustered at the city level. If the parallel trends assumption holds, the estimated μ_k should not be statistically different from 0 when k is negative.

4.3 Triple Difference

We conduct two distinct triple-difference estimations. First, we classified industries into heavily polluting, moderately polluting, and lightly polluting industries (including those with minimal pollution). While both heavily polluting and moderately polluting industries could be impacted by the strengthened environmental regulations, we anticipate that heavily polluting industries will experience more significant effects. Accordingly, we estimate the following equation:

$$Accident_{cit} = \beta Post2014_t \times Pollution_i \times HeavyPollution_i + \alpha_{ci} + \alpha_{it} + \alpha_{ct} + \epsilon_{cit}, \tag{3}$$

where c, t and i represents prefecture-level city, year, and industry type as above. $HeavyPollution_i$ is a dummy indicating heavily polluting industries. $Pollution_i$ is a dummy indicating heavily and moderately polluting industries. In addition to city-by-industry type fixed effects (α_{ci}) and city-by-year fixed effects (α_{ct}), which are controlled for in the difference-in-differences model, we also include industry type-by-year fixed effects (α_{it}). Standard errors are clustered at the city level. The coefficient β captures the differential effects of environmental regulations on industrial accidents in heavily polluting industries compared with moderately polluting industries. A significantly positive β suggests that stricter environmental regulations result in a greater increase in accidents in heavily polluting industries compared to moderately polluting industries.

Second, the intensity of environmental regulations varied across cities. According to the central government's guidelines, regulations were implemented more stringently in the 47 "Key-Control Cities," where special pollution limits were imposed and environmental entry requirements were stricter. Faced with these tougher regulations, polluting firms in these cities may have experienced greater pressure and were thus more likely to reallocate resources from safety investments to pollution reduction.[9]

[9] Such variations in the implementation intensity of environmental regulations across regions may incentivize firms to relocate to cities with lower regulatory pressures. However, given that relocating takes time and incurs significant costs, and considering that our sample period is within 3 years following the tightened regulations, this factor is unlikely

Exploiting the spatial variation of intensity, we conduct a triple difference estimation and explore the heterogeneous effects of regulations across cities. Specifically, we estimate the following equation:

$$Accident_{cit} = \beta Post2014_t \times Pollution_i \times Keycity_c + \alpha_{ci} + \alpha_{it} + \alpha_{ct} + \epsilon_{cit}, \tag{4}$$

where c, t and i represents prefecture-level city, year, and industry type as above. $Keycity_c$ is an indicator variable that takes the value 1 for cities included in the list of 47 "Key-Control Cities," and 0 otherwise. Fixed effects are the same as those in Equation 3. Standard errors are clustered at the city level again. The coefficient of interest is β, which captures the differential change of accidents in pollution-intensive industries after 2014 between the 47 "Key-Control Cities" and the remaining ones. A significantly positive β suggests that cities facing stricter environmental regulations experienced a higher relative increase in accidents in pollution-intensive industries, which is consistent with our hypothesis.

5 Results

5.1 Main Results

We begin by presenting the results of our difference-in-differences estimation in Table 2, which aims to establish causal evidence on whether strengthened environmental regulations lead to an increase in industrial accidents. In columns (1) and (2) of this table, the treatment group consists of heavily and moderately polluting industries, classified as pollution-intensive, while the control group comprises lightly polluting industries. In columns (3) and (4), the treatment group includes heavily polluting industries, with the control group comprising moderately and lightly polluting industries. In column (1) and (3) of this table, we present the estimates with year fixed effects and city-by-industry type fixed effects. In column (2) and (4), we report the estimates from our

to pose a serious threat to the validity for our analysis. Furthermore, if polluting firms were to relocate out of the "Key-Control Cities," it is likely to reduce industrial accidents in these cities, making it less likely to observe significant triple-difference estimates.

Table 2: DID Estimates of the Effect of Environmental Regulations on Industrial Accidents

Dependent Variable:	Number of Accidents			
	(1)	(2)	(3)	(4)
Post2014 × Pollution	0.084***	0.084***	0.172***	0.172***
	(0.028)	(0.028)	(0.031)	(0.031)
Year FE	YES	NO	YES	NO
City × Pollution FE	YES	YES	YES	YES
City × Year FE	NO	YES	NO	YES
Observations	5,760	5,760	5,760	5,760
R^2	0.365	0.726	0.391	0.732
Mean Dependent Var.	0.285	0.285	0.285	0.285

Notes: This table reports the DID estimates of the effect of environmental regulations on industrial accidents, specifically presenting the coefficient β from Equation (1). In columns (1) and (2), the treatment group consists of heavily and moderately polluting industries, classified as pollution-intensive, while the control group comprises lightly polluting industries. In columns (3) and (4), the treatment group includes heavily polluting industries, with the control group comprising moderately and lightly polluting industries. Specifications in columns (1) and (3) include year fixed effects and city-by-industry-type fixed effects, and specifications in columns (2) and (4) include city-by-industry-type fixed effects and city-by-year fixed effects. Standard errors in parentheses are clustered at the city level. * p<0.1; ** p<0.05; *** p<0.01.

preferred specification, which controls for both city-by-industry type fixed effects and city-by-year fixed effects.

According to our preferred specification, the coefficient of interest is 0.172 and is significant at the 0.01 level. This indicates that, on average, each city experienced 0.172 more accidents per year in heavily polluting industries compared to other industries after 2014.[10] Given that the mean annual number of accidents across all cities is 0.285, this estimate represents an increase of approximately 60.4% (0.172/0.285) relative to the mean value. This finding suggests a substantial impact of the strengthened regulations on industrial accidents.

In our baseline estimation, we use the number of industrial accidents as the outcome variable. Additionally, stricter environmental regulations may increase fatalities caused by industrial accidents in pollution-intensive industries compared to non-pollution-intensive industries. Building on the baseline estimation, we provide additional results by replacing the number of industrial

[10] Our estimates in columns (3) and (4) are highly similar, which may be because the city-by-year fixed effects add little additional information once city-by-industry and year fixed effects are already included. If the identification of the treatment effect primarily depends on differences between industries rather than city-specific or year-specific factors, this would explain the near-identical results.

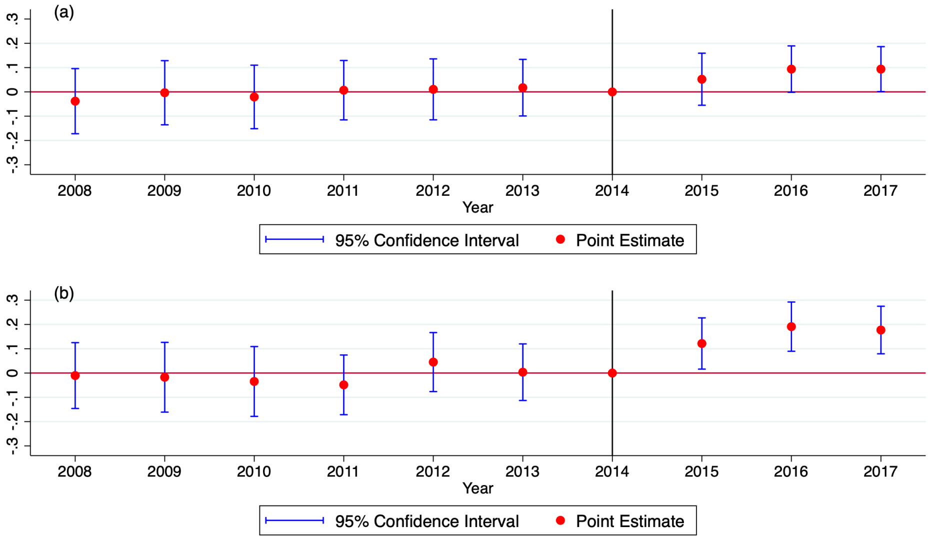
accidents with the number of fatalities as the outcome variable. The results, presented in Table A.4, confirm our expectations: after 2014, the number of fatalities caused by industrial accidents in pollution-intensive industries is significantly higher than in non-pollution-intensive industries.

To validate the common trends assumption of our difference-in-differences strategy, we estimate Equation 2 and present the event-study results in Figure 4. Evidently, the time indicators prior to 2014 are close to zero, suggesting that the number of industrial accidents in pollution-intensive and non-pollution-intensive industries followed a common trend prior to the treatment. After 2014, the difference in industrial accidents between pollution-intensive and non-pollution-intensive industries begins to increase. In summary, the event-study results further validate our pre-trend assumption and suggest that accidents in pollution-intensive industries became more frequent than accidents in non-pollution-intensive industries following the strengthened regulations in 2014.

Then, we present the estimates from the two triple-difference estimations. We begin with the triple-difference analysis based on pollution levels. We expect that heavily polluting industries are more significantly impacted by the strengthened environmental regulations compared to moderately polluting industries. The estimation results of the equation are presented in Table 3. In column (1), we report the estimates while controlling for city-by-industry-type fixed effects and industry-type-by-year fixed effects. In column (2), we further include city-by-year fixed effects, which represents our preferred specification. The results indicate an additional 0.097 annual industrial accidents in heavily polluting industries compared to moderately polluting industries, aligning with our expectations.

Finally, we present the results of the triple-difference analysis based on whether cities are classified as "Key-Control Cities." Given that the regulations were enforced more strictly in the 47 so-called "Key-Control Cities," we expect the impacts of the strengthened regulations to be more pronounced in these cities compared to others. The results of the triple difference estimation in Equation 4 are displayed in Table 4. Pollution-intensive industries are heavily polluting industries, and non-pollution-intensive industries are other industries. In column (1), we report the estimates while controlling for city-by-industry type fixed effects and industry type-by-year fixed effects.

Figure 4: Event Study Estimates: Dynamic Effects of Environmental Regulations on Industrial Accidents across Cities



Notes: This figure illustrates the dynamic coefficients obtained from the estimation of Equation 2 together with 95% confidence intervals. In Panel (a), the treatment group consists of heavily and moderately polluting industries, classified as pollution-intensive, while the control group comprises lightly polluting industries. In Panel (b), the treatment group includes heavily polluting industries, with the control group comprising moderately and lightly polluting industries. City-by-industry-type fixed effects and city-by-year fixed effects are included in both panels.

Table 3: Triple Difference: Differential Effects of Environmental Regulations across Pollution Levels

Dependent Variable:	Number of Accidents	
	(1)	(2)
Post2014 × Pollution× HeavyPollution	0.097***	0.097***
	(0.018)	(0.018)
City × Pollution FE	YES	YES
Year × Pollution FE	YES	YES
City × Year FE	NO	YES
Observations	8,640	8,640
R^2	0.315	0.542
Mean Dependent Var.	0.190	0.190

Notes: This table reports the triple-difference estimates of the differential effect of environmental regulations across pollution levels, specifically presenting the coefficient β from estimating Equation (3). The specification in column (1) includes city-by-industry-type fixed effects, year-by-industry-type fixed effects. The specification in column (2) further includes city-by-year fixed effects. Standard errors in parentheses are clustered at the city level. * p<0.1; ** p<0.05; *** p<0.01.

In column (2), we additionally control for city-by-year fixed effects, which is our preferred specification. The results show that the triple difference coefficient is approximately 0.466 and significant at the 0.01 level, indicating that the impact of the regulations on industrial accidents is substantially larger in "Key-Control Cities."

5.2 Robustness

In this section, we test the robustness of our estimates. Since our outcome variable is a count variable, we begin by testing the robustness of our results using Poisson regressions and negative binomial regressions. The results of these quick robustness tests are presented in Table A.5 and Table A.6, respectively. These results are consistent with our baseline findings.

A major concern in our analysis is data reliability. Our main results rely on data from news reports, which are generally immune to the ex-post manipulation often observed in China's official data (Ghanem and Zhang, 2014; Wallace, 2016; Fisman and Wang, 2015). However, news data also have their limitations. The total number of accidents may be underestimated if some accidents go unreported by the news media. In particular, increasingly strict state control over media resources in China may result in a significant underestimation of accidents.

Table 4: Triple Difference: Differential Effects of Environmental Regulation across Cities

Dependent Variable:	Number of Accidents	
	(1)	(2)
Post2014× Pollution × Keycity	0.466***	0.466***
	(0.130)	(0.130)
Post2014 × Keycity	-0.529***	
	(0.140)	
City × Pollution FE	YES	YES
Year × Pollution FE	YES	YES
City × Year FE	NO	YES
Observations	5,760	5,760
R^2	0.400	0.736
Mean Dependent Var.	0.285	0.285

Notes: This table reports the triple-difference estimates of the differential effect of environmental regulations on industrial accidents in "Key Control Cities" compared with other cities, specifically presenting the coefficient β from Equation (4). The treatment group consists of heavily polluting industries, while the control group comprises moderately and lightly polluting industries. The specification in column (1) includes the interaction term between $Keycity$ and $Post2014$ indicator, city-by-industry-type fixed effects, and year-by-industry-type fixed effects. The specification in column (2) further includes city-by-year fixed effects. Standard errors in parentheses are clustered at the city level. * p<0.1; ** p<0.05; *** p<0.01.

We address this concern in several ways. First, although some accident reports are missed due to media censorship, our estimates would remain unbiased as long as there is no selective reporting according to industry types. Given that the primary goal of media censorship is to maintain state stability and prevent social unrest, it is unlikely that the industry type of an accident would influence whether it is reported. Essentially, any selection bias would most likely be based on the severity of accidents. As long as this assumption holds, there is no reason to worry that media censorship would bias our estimates.

We now address the issue of potential selection bias arising from media control due to accident severity. Arguably, media censorship may selectively report accidents based on severity, omitting minor accidents and only reporting those of such a magnitude that they cannot be concealed. As shown in Table 1, the largest accidents in pollution-intensive industries result in significantly more fatalities than the largest accidents in non-pollution-intensive industries. Therefore, it is plausible that accidents in non-pollution-intensive industries are systematically underreported in comparison to accidents in pollution-intensive industries, potentially biasing our estimates upward.

To address this concern, we restrict our sample to accidents causing no more than three fatalities, which are officially defined as "Ordinary Accidents" in China. Intuitively, if a relative increase of accidents in pollution-intensive industries is observed even among these modest accidents, the concern over selection bias can be alleviated. The results are shown in Table A.7, where we demonstrate that similar patterns hold even when considering only ordinary accidents, thereby mitigating the selection issue.

To further address the potential issue of underreporting, we complement our data with another dataset: the official accident records publicized by SAWS. We merge the two datasets, omitting accidents that are recorded in both to avoid duplication. While official data are undeniably dampened by manipulation (Fisman and Wang, 2015, 2017), they can serve as a useful complement for the news data. The results from the consolidated dataset are shown in Table A.8. In the first two columns, we present the estimates based solely on data from SAWS. In column (3) and column (4), we present the estimates using the merged dataset from WiseNews and SAWS. These results align with our baseline results, further validating the robustness of our findings.

We have so far demonstrated that our estimates are unlikely to be biased by potential underreporting of industrial accidents. However, concerns may still arise regarding the representativeness of our data. Essentially, news data could have other limitations that we may not fully account for. For example, some might argue that media outlets disproportionately cover certain regions, particularly more developed ones, over others. Nevertheless, our results should remain unbiased as long as this regional focus does not shift following the implementation of the strengthened environmental regulations.

Finally, one might be concerned that our difference-in-differences estimation could be biased due to negative weights, as discussed by De Chaisemartin and d'Haultfoeuille (2020). In our context, however, stricter environmental regulations were implemented simultaneously across all cities in 2014, reducing the likelihood of this issue. To formally address this concern, we use the command developed by De Chaisemartin and d'Haultfoeuille (2020) to compute the number of average treatment effects on the treated (ATTs) receiving negative weights, and we find that this number is 0.[11] Therefore, negative weights should not be a concern in our analysis.[12]

5.3 Suggestive Firm-level Evidence

We now further conduct firm-level analyses to investigate the effects of strengthened environmental regulations on industrial accidents more granularly. These analyses complement our prefecture level analysis and provide deeper insights into the factors contributing the deterioration of workplace safety.

The strengthened regulations may impact all firms within pollution-intensive industries, as they likely face increased pressure and are forced to reallocate more resources toward pollution control, potentially at the expense of workplace safety. Actual penalties for environmental violations should exacerbate financial constraints and further intensify the pressure to address pollution. Specifically, we examine (i) whether industrial accidents became more likely in firms within pollution-intensive industries following the implementation of the revised EPL in 2014, and (ii) whether accidents are more likely after these firms are penalized for environmental regulation violations.

We first construct a firm-level panel dataset of industrial accidents. From our city-level accident data, we identify the related firms based on the descriptions of incidents. Overall, we compile a dataset of 1,443 unique firms that experienced accidents from 2008 to 2017. We then collect additional information on these firms from Tianyancha, a major business search platform that covers the universe of Chinese firms. Of particular interest is whether, and when, the firms were penalized for environmental violations. We find that, among the 1,443 firms, 371 had records of environmental penalties.

Our analysis is two-folded. First, we assume that the strengthened environmental regulations may impact all firms within pollution-intensive industries, regardless of whether they have been penalized. Similar to our baseline analysis, we employ a difference-in-differences strategy to examine whether accidents are more likely to occur in polluting firms after 2014. Specifically, we estimate the following equation:

[11] The Stata command is: twowayfeweights

[12] Our results remain robust when applying their method to conduct the regressions.

$$Accident_{jt} = \beta Post2014_t \times Pollution_j + \alpha_j + \alpha_t + \epsilon_{jt}, \tag{5}$$

The dependent variable $Accident_{jt}$ is a dummy variable indicating whether an accident has occurred, taking the value 1 if one or more accidents have occurred in firm j, and 0 otherwise.[13] $Pollution_j$ is a dummy taking the value 1 when firm j belongs to pollution-intensive industries, and 0 otherwise. α_j represents firm fixed effects, accounting for time-invariant firm-level characteristics that may influence the occurrence of industrial accidents. α_t represents year fixed effects. Standard errors are clustered at the firm level.

Our results are displayed in column (1) of Table A.9. We find that after controlling for year and firm fixed effects, firms in pollution-intensive industries are significantly more likely to experience accidents after 2014 compared to firms in non-pollution-intensive industries. This finding aligns with our hypothesis that strengthened environmental regulations affect all firms within pollution-intensive industries, regardless of whether they have been penalized. To test the parallel trends assumption, we employ an event study approach by estimating Equation 6 below and present the dynamics of the coefficients in Figure A.1. We find that the coefficients are not statistically different from zero prior to 2014, which supports the parallel trends assumption.

$$Accident_{jt} = \sum_{k=-6}^{k=-1} \mu_k \times Pollution_j + \sum_{k=1}^{k=3} \mu_k \times Pollution_j + \alpha_j + \alpha_t + \epsilon_{jt}, \tag{6}$$

Second, we examine the impact of actual penalties for environmental regulation violations on firm-level industrial accidents. We hypothesize that accidents are more likely to occur after firms are penalized for excessive pollution. To test this, we employ a staggered difference-in-differences strategy and estimate the following equation.

$$Accident_{jt} = \beta PostPenalty_{jt} + \alpha_j + \alpha_t + \epsilon_{jt}, \tag{7}$$

$PostPenalty_{jt}$ is an indicator variable taking 1 for all years after the first environmental penalty

[13] Few firms experienced more than one accident.

at firm j, and 0 otherwise. All other notations are the same as in Equation 6. The treatment group consists of polluting firms that experienced penalties during the period 2008-2017, and the control group comprises non-polluting firms which, naturally, were not subject to penalties. Standard errors are clustered at the firm level.

Our results are shown in column (2) of Table A.9. We find that industrial accidents are significantly more likely to occur after firms are penalized, with year and firm fixed effects controlled. To test the parallel trends assumption, we also use an event study approach by estimating Equation 8. Figure A.2 illustrates the dynamic effects of penalties on accidents. While the coefficients are indistinguishable from zero before the penalty, they become significantly positive afterward. These firm-level analyses complement our city-level analysis and bolster our confidence that the strengthened environmental regulations in 2014, particularly the penalties for violations, contributed to an increase in industrial accidents.

$$Accident_{jt} = \sum_{k=-6}^{k=-1} \mu_k \times Penalty_j + \sum_{k=1}^{k=3} \mu_k \times Penalty_j + \alpha_j + \alpha_t + \epsilon_{jt}, \tag{8}$$

6 Mechanisms

6.1 Decreased Safety Investments

In this section, we examine the mechanisms through which environmental regulations contribute to the increase in industrial accidents. As discussed earlier, Stricter environmental regulations may have imposed significant financial constraints on pollution-intensive firms, forcing them to allocate more resources toward addressing pollution at the expense of safety investments. This shift in resource allocation could potentially increase the risk of industrial accidents. To investigate this, we use data on publicly listed firms from CSMAR, which provides detailed information on firms' safety expenditures from 2008 to 2017. We employ a difference-in-differences strategy, with firms in heavily polluting industries as the treatment group and firms in moderately and lightly polluting industries as the control group, to examine whether the former reduced their safety expenditures following the implementation of stricter environmental regulations compared to the latter. Specifically, we estimate the following equation:

$$lnsafeexp_{it} = \beta Post2014_t \times Pollution_j + \gamma lnasset_{it} + \alpha_i + \alpha_{cj} + \alpha_{ct} + \alpha_{et} + \epsilon_{it}, \qquad (9)$$

where i and t represent firm and year, respectively; j represents industry type. $lnsafeexp_{it}$ measures safety expenditures, which are proxied by special reserves allocated for safety production costs.[14] $Post2014$ is a dummy variable that takes the value of 1 for years after 2014, the year when environmental regulations were strengthened. $Pollution_j$ is a dummy variable indicating pollution-intensive industries, defined as heavily polluting industries. $lnasset_{it}$ represents the natural logarithm of the total assets of firm i in year t. α_i represents firm fixed effects. In our preferred specification, we include city-by-industry type fixed effects (α_{cj}) and city-by-year fixed effects (α_{ct}). Cities refer to the locations where the headquarters of listed firms are situated. Since there are several types of firms—domestic private firms, state-owned firms, foreign-invested firms, and others—we also control for firm type-by-year fixed effects (α_{et}). Standard errors are clustered at the firm level.

Table 5 presents our estimates. As shown, the coefficients are negative across all columns as additional control and fixed effects are included. These findings suggest that firms in pollution-intensive industries reduce their safety expenditures following the enactment of stricter environmental regulations, compared to firms in non-pollution-intensive industries. This reduction in safety expenditures may help explain the observed increase in industrial accidents within pollution-intensive industries after 2014.

To validate the parallel trends assumption, we adopt an event study approach. Specifically, we estimate the following equation to capture the dynamics of safety expenditures both before and after the implementation of stricter environmental regulations.

[14] The functional form used is ln(1+safety expenditures) because some safety expenditures are zero. However, we acknowledge that this approach might be problematic (Chen and Roth, 2024). To address this, we considered using only positive safety expenditures and applying the functional form ln(safety expenditures). The results remain robust.

Table 5: DID Estimates of the Effect of Environmental Regulations on Firms' Safety Expenditures

Dependent Variable:	ln(Safety Expenditures)		
	(1)	(2)	(3)
Post2014 × Pollution	-0.558***	-0.402***	-0.386**
	(0.131)	(0.129)	(0.170)
Control	NO	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	NO
City × Pollution FE	NO	NO	YES
City × Year FE	NO	NO	YES
Firm type × Year FE	NO	NO	YES
Observations	11,199	11,199	9,731
R^2	0.869	0.873	0.895
Mean Dependent Var.	2.917	2.917	2.763

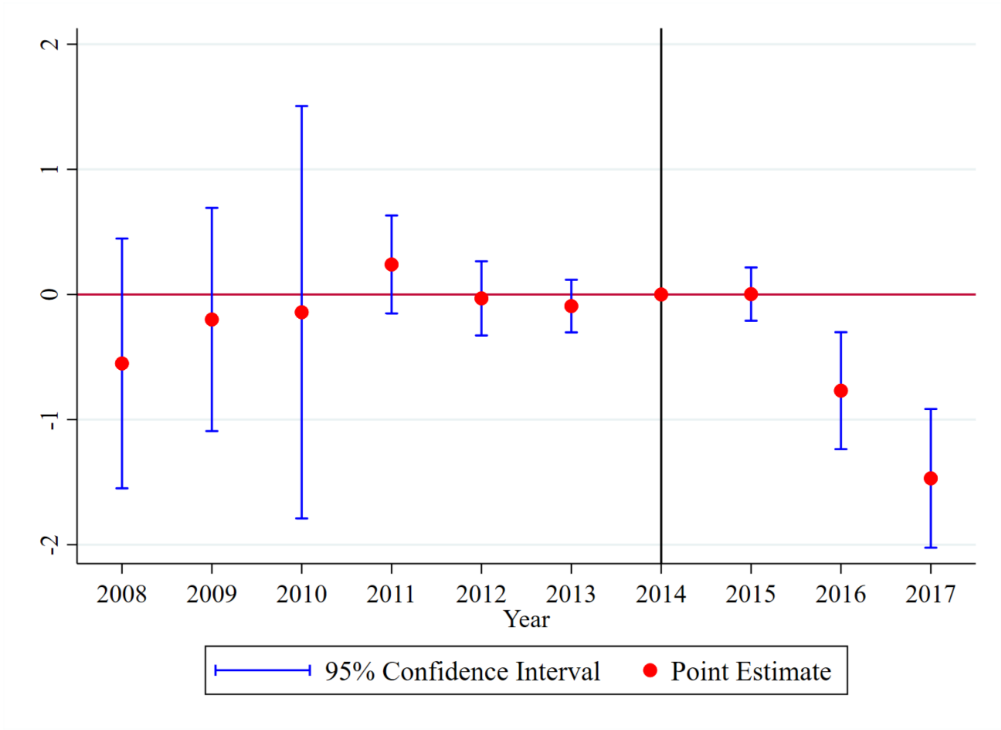
Notes: This table reports the DID estimates of the effect of environmental regulations on firms' safety expenditures, specifically presenting the coefficient β from Equation (9). The treatment group consists of heavily polluting industries, classified as pollution-intensive, while the control group comprises moderately and lightly polluting industries. Column (1) includes firm fixed effects and year fixed effects. Column (2) includes firm fixed effects, year fixed effects, and the control variable $ln(asset)$. Column (3) further includes city-by-industry type fixed effects, city-by-year fixed effects, and firm type-by-year fixed effects. Standard errors in parentheses are clustered at the firm level. * p<0.1; ** p<0.05; *** p<0.01.

$$lnsafeexp_{it} = \sum_{k=-6}^{k=-1} \mu_k \times Pollution_j + \sum_{k=1}^{k=3} \mu_k \times Pollution_j + \gamma lnasset_{it} + \alpha_i + \alpha_{cj} + \alpha_{ct} + \alpha_{et} + \epsilon_{it}, \quad (10)$$

where μ_k captures the relative event-time indicators. That is, μ_k is an indicator variable that takes the value 1 if it is k years relative to 2014. As is typical in the event study frameworks, we make the normalization $\mu_0 = 0$, so that all coefficients represent differences in accidents relative to the year 2014. Other notations are consistent with those in Equation 9. Please note that we include the same control variable and fixed effects as specified in Equation 9.

As shown in Figure 5, the time indicators prior to 2014 are close to zero, suggesting that safety expenditures in pollution-intensive and non-pollution-intensive industries were very similar before the treatment. After 2014, safety expenditures in pollution-intensive industries began to decline relative to those in non-pollution-intensive industries. This evidence supports the parallel trends assumption and suggests that pollution-intensive industries responded to the implementation of stricter environmental regulations by reducing their safety expenditures.

Figure 5: Event Study Estimates: Dynamic Effects of Environmental Regulations on Safety Expenditures



Notes: This figure illustrates the dynamic coefficients obtained from the estimation of Equation 10 together with 95% confidence intervals. The treatment group includes heavily polluting industries, while the control group consists of moderately and lightly polluting industries. City-by-industry type fixed effects, city-by-year fixed effects, firm type-by-year fixed effects, and the control variable are included.

Our sample is limited to publicly listed firms because they provide detailed information on safety expenditures. To provide additional evidence, we show that a reduction in profits leads to decreased safety investments by firms, using data from the Annual Survey of Industrial Firms (ASIF). Details are provided in Section A.1 of the Appendix.

6.2 Alternative Mechanisms

In this section, we briefly discuss alternative potential mechanisms through which environmental regulations could impact industrial accidents. We show that none of these alternative mechanisms undermines our primary explanation.

1. Reduced Quantities and Scales of Firms

Environmental regulations may negatively affect both the number and size of pollution-related firms. Incumbent firms might respond by scaling down production, leading some struggling firms to exit the industry. Additionally, stricter regulations raise the bar for survival, hindering potential new entrants. This reduction in the number and scale of polluting firms would naturally result in a decline in accidents in pollution-intensive industries. However, contrary to this expectation, we document a relative increase in the number of such accidents, which clearly cannot be attributed to the reduced number and scale of polluting firms.

2. Improved Cognitive Performance

Regulations could positively influence workers' cognitive performance by improved air quality. Recent studies have confirmed that air pollution has adverse effects on cognitive performance and can trigger more accidents (Lavy et al., 2022; Sager, 2019). In our context, the remarkable improvement in air quality following the regulations should presumably enhance workers' cognitive performance, thereby reducing accidents in pollution-intensive industries. Hence, improved cognitive performance does not account for our findings.

3. Stress and Fatigue

Strengthened environmental regulations may increase stress and fatigue among workers in pollution-intensive industries. First, these regulations raise firms' overall costs, requiring investments in cleaner technologies and internalizing pollution control expenses. To offset these costs, firms may reduce other expenditures, such as halting recruitment and requiring employees to work overtime. Second, stricter regulations can lead to layoffs, as documented in the literature, with higher unemployment resulting from environmental policies (Greenstone, 2002; Curtis, 2018). Consequently, remaining workers may feel increased pressure and opt to work overtime. Overtime work tends to reduce caution among workers, potentially increasing the likelihood of industrial accidents (Boone et al., 2011). Additionally, Tan et al. (2021) document that overtime work is a significant factor contributing to the rise in industrial accidents in China. Therefore, stress and fatigue could be a possible alternative mechanism explaining our main findings. Specifically, more severe financial constraints imposed by environmental regulations may have forced polluting firms to adjust their operational strategies, ultimately leading to an increase in industrial accidents.

4. Disrupted Production and Disorganized Management Practice

The importance of management practice on workplace outcomes has been well-documented (Bloom et al., 2012, 2013). Numerous reports of accidents in pollution-intensive industries suggest that firms experienced production suspensions prior to the accidents (e.g. Xiangshui Explosion, 2019), which could disrupt the well-established management practices in these firms. Upon resuming production, firms may operate in a more disorganized manner, potentially leading to more accidents. While disrupted production and disorganized management are unlikely to be the primary reasons for the surge in accidents-since only a small fraction of firms experienced temporary production halts-they may still represent a side effect of environmental regulations, which could negatively affect industrial safety.

5. Outdated Equipment

Some of the immediate causes of industrial accidents stem from the continued use of outdated equipment, which fails to meet safety standards and poses significant risks. According to an analysis of major chemical and hazardous chemical accidents in China between 2011 and 2020, 7% of these accidents involved outdated equipment.[15] For example, in November 2018, a petrochemical

[15] http://www.jshgjt.com/a/xinwenzhongxin/xingyexinwen/2493.html

transport vessel leaked 69.1 tons of C9 products near the coast at Quanzhou Port, Fujian, causing water pollution. According to the report from the petrochemical company involved, the leakage resulted from aging and damaged hose gaskets during loading and unloading operations, marking this incident as a typical case of a "man-made disaster." One major reason for the continued use of aging equipment without timely upgrades is financial constraints, which have become more pronounced as environmental regulations have tightened. This aligns with our previous discussion on how stricter environmental regulations can lead to reduced investments in production safety.

7 Conclusion

Industrial disasters in pollution-intensive industries often have far-reaching and devastating consequences. These incidents not only jeopardize the health and safety of workers but also pose significant risks to nearby residents and cause extensive damage to surrounding infrastructure. This study examines the unintended consequences of environmental regulations on industrial accidents, with important implications for welfare and policy. Leveraging the unique context of China's implementation of the revised EPL, this paper finds that the number of industrial accidents in pollution-intensive industries increased relative to non-pollution-intensive industries within the same city, following the enactment of stricter environmental regulations. Furthermore, we demonstrate that the reduction in firms' safety investments, driven by tighter financial constraints following the implementation of stricter environmental regulations, is a plausible underlying mechanism. This finding suggests that the potential welfare distortion could be substantial: when firms determine safety investments, they primarily consider the potential losses to themselves, often overlooking the potentially significant societal costs. As a result, equilibrium safety investments fall far below the socially optimal level.

Our findings have profound implications given the global adoption of environmental regulations. While these regulations are designed to address externalities and enhance social welfare, our analysis shows that they may inadvertently lead to an increase in industrial accidents, thereby undermining welfare gains. This suggests that traditional cost-benefit analyses of environmental regulations might significantly underestimate their societal costs. It is important to note that we do not argue against the implementation of environmental regulations. The key takeaway for policymakers is to exercise caution when designing such regulations, as they may lead to unforeseen consequences and potentially backfire.

Our findings could be particularly relevant for developing countries where manufacturing industries are pivotal for economic growth and working conditions remain poor, such as China, India, and Vietnam. In these countries, economic growth is often prioritized, but governments also face multifaceted challenges, including environmental degradation and fragile workplace safety. Ideally, an optimal regulatory policy should balance multiple objectives. Our paper suggests that policies overly focused on a single domain—while neglecting other dimensions—can be problematic.

The broad societal implications of environmental regulations and other industrial policies warrant further exploration in future research. For instance, environmental regulations may crowd out investments in other sectors, affecting firms' resource allocation and potentially leading to additional welfare consequences. Moreover, well-intentioned government interventions can sometimes produce unintended negative outcomes due to information gaps or capacity constraints. Future research is needed to identify these unforeseen effects and mitigate the risk of government failure.

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Appendix A Appendix

A.1 Decreased Safety Investments: Evidence from Annual Survey of Industrial Firms

Although we provide solid evidence of the reduction in safety expenditures among pollution-intensive firms after 2014 in Section 6, one might be concerned that this analysis is limited to publicly listed firms. We focus on these firms because they provide detailed information on safety expenditures during our sample period, 2008 to 2017. However, they may not be fully representative. To offer additional evidence on reductions in safety investments within pollution-intensive industries, we employ an alternative dataset: the Annual Survey of Industrial Firms (ASIF). The ASIF dataset includes variables that can be proxies of safety investments during the period 2000 to 2007.[16] While it cannot be used to directly test whether stricter environmental regulations implemented in 2014 led to a decline in safety investments, it can be utilized to examine whether a reduction in profits results in decreased safety investments by firms.

A large body of literature has demonstrated that environmental regulations negatively impact firms' profits (e.g., Greenstone, 2002; Dean et al., 2009; Rassier and Earnhart, 2010; Fan et al., 2019). To comply with these regulations, polluting firms may reduce outputs or upgrade to cleaner technologies, both of which incur considerable economic costs (Karplus et al., 2021). If reduced profits lead to lower safety investments, it is reasonable to expect that environmental regulations result in firms' reduced safety investments due to diminished profits.[17] Consequently, we investigate whether a decline in profits leads to a reduction in firms' safety investments. A positive correlation between profits and safety investments at the firm level would suggest that reduced safety investments serve as an important mechanism in this context.

Firms' safety investments include intangible investments like employee training, monitoring and enforcing safety compliance, and fostering a culture that values safety (Cohn and Wardlaw, 2016).

[16] The statistical standards of the ASIF changed in 2008.

[17] There are also studies using U.S. data that suggest when firms' profits are lower, workplace safety outcomes tend to worsen (Rose, 1990; Asfaw et al., 2013; Amin et al., 2021).

Accordingly, one of our proxies for safety investments is expenditures on employee training. Not only are safety investments vulnerable and likely to be sacrificed, but some other types of investments that seem less urgent in the short run may also be cut due to regulatory pressures. While such investments may not be directly linked with compromised workplace safety, they can help us better understand firms' broader investment patterns when facing regulations. To this end, we further explore the relationship between expenditures on insurance-a type of precautionary expenditure-and firms' profits. Although precautionary expenditures like insurance may not generate immediate value, they play a crucial role in mitigating potential risks and safeguarding employee welfare. However, in the face of financial shocks, insurance expenditures may also be vulnerable as well. We thus examine whether a decline in profits leads to a reduction in firms' insurance expenditures.

The results are displayed in Table A.1. We consistently control for year fixed effects and firm fixed effects to account for year-specific shocks and time-invariant firm-level characteristics that could influence safety investments. In columns (1) and (2), the outcome variable is expenditure on employee training. In columns (3) and (4), the outcome variable is insurance expenditure. The odd-numbered columns include no additional controls, while the even-numbered columns control for firm assets.

As shown, we find that the expenditure on employee training is positively correlated with firms' profits. This suggests that firms' investments in employee training decrease significantly as profits decline. Given that firms' profits are highly likely to decline due to strengthened environmental regulations, as suggested by previous literature, our findings support the hypothesis that environmental regulations negatively affect firms' profits, crowding out safety investments and leading to an increase in industrial accidents. Additionally, as shown in columns (3) and (4), we observe that insurance expenditures also decrease when profits decline. This suggests that firms might respond to environmental regulations by cutting back on investments that may be perceived as non-urgent, if environmental regulations negatively affect their profits.

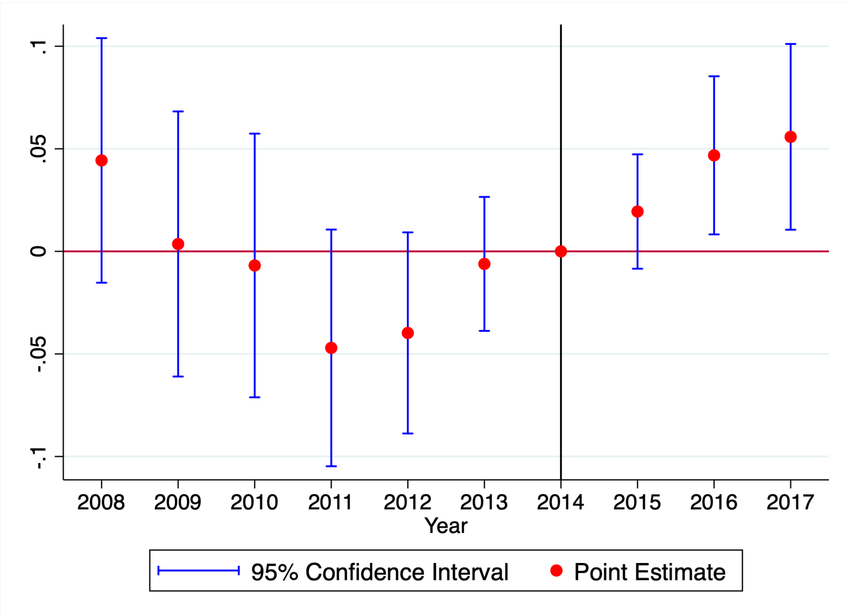
A.2 Figures and Tables

Table A.1: Correlation between Profits and Safety Investments at the Firm Level

Dependent Variable:	ln (Training Expenditures)		ln (Insurance Expenditures)	
	(1)	(2)	(3)	(4)
ln (Profits)	0.011***	0.008***	0.015***	0.013***
	(0.000)	(0.000)	(0.000)	(0.000)
ln (Assets)	NO	YES	NO	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	1,081,017	1,080,744	2,084,835	2,084,565
R^2	0.693	0.695	0.578	0.582
Mean Dependent Var.	1.285	1.285	1.289	1.289

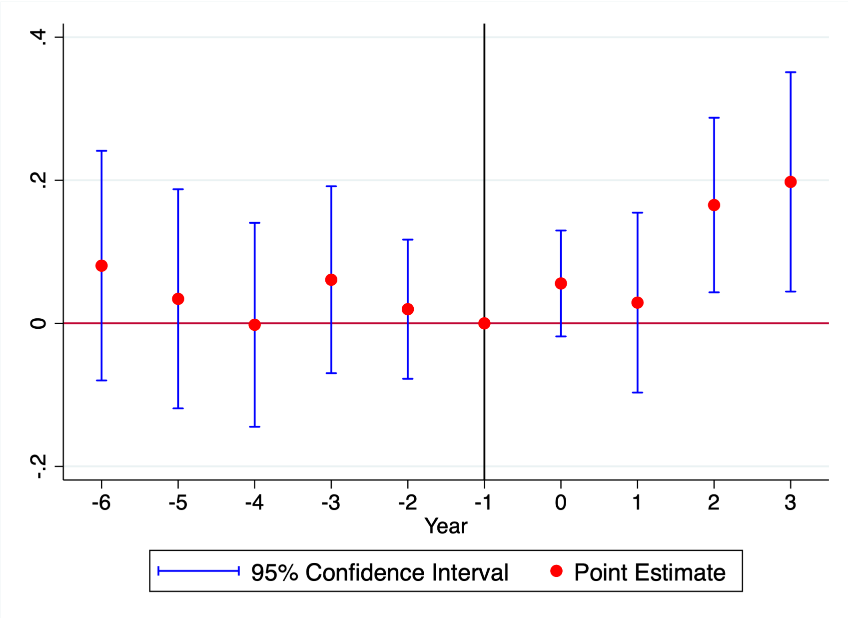
Notes: This table illustrates the relationship between profits and safety investments at the firm level, using ASIF data for the period 2000-2007. The specification is $ln(SafetyInvestments)_{it} = \beta ln(Profits)_{it} + \gamma X_{it} + \alpha_i + \alpha_t + \epsilon_{it}$. Dependent variables in columns (1) and (2) refer to the log of firms' total training expenditures, and columns (3) and (4) refer to the log of firms' total insurance expenditures. All specifications include year fixed effects and firm fixed effects, and columns (2) and (4) control for the log of firms' assets. Standard errors in parentheses are clustered at the firm level. * p<0.1; ** p<0.05; *** p<0.01.

Figure A.1: Event Study Estimates: Dynamic Effects of Environmental Regulations on Industrial Accidents at the Firm Level



Notes: This figure illustrates the dynamic coefficients obtained from the estimation of Equation 6 together with 95% confidence intervals. The sample includes all firms that experienced at least one documented industrial accident in WiseNews and were identifiable from news reports. The treatment group includes firms classified as heavily polluting industries, and the control group comprises firms classified as moderately and lightly polluting industries. Year fixed effects and firm fixed effects are included.

Figure A.2: Event Study Estimates: Dynamic Effects of Environmental Penalty on Industrial Accidents at the Firm Level



Notes: This figure illustrates the dynamic coefficients obtained from the estimation of Equation 8 with 95% confidence intervals. The sample includes all firms that experienced at least one documented industrial accident in WiseNews and were identifiable from news reports. The treatment group includes the heavily polluting firms that experienced at least one environmental penalty documented by Tianyancha, and the control group comprises firms of moderately and lightly polluting industries. The time variable is the year when a firm was penalized for environmental reasons for the first time, and the window [-6,+3] is covered around the penalty year. Year fixed effects and firm fixed effects are included.

Table A.2: Major Industrial Accidents with Fatalities Exceeding 60 in China, 2008-2017

Date	City	Enterprise	Deaths	Direct property losses ($\times 10^4$ RMB)
3 Jun 2013	Dehui	Baoyuanfeng poultry	121	18,200.00
22 Nov 2013	Qingdao	SINOPEC	62	750,000.00
2 Aug 2014	Suzhou	Zhongrong metal products	97	35,100.00
12 Aug 2015	Tianjin	Tianjin port	173	686,600.00
24 Nov 2016	Fengcheng	Fengcheng power plant	74	10,197.20

Notes: This table documents major industrial accidents with more than 60 fatalities in China during 2008-2017. based on data from State Administration of Work Safety (SAWS) and WiseNews. No industrial accidents resulted in more than 60 deaths between 2008 and 2012.

Table A.3: Classification of Industries by Pollution Intensity

Heavily Polluting Industries		Moderately Polluting Industries	
Industry	Code	Industry	Code
Coal mining and processing	6	Oil extraction	7
Ferrous metal ore mining	8	Non-metallic mineral mining	10
Non-ferrous metal ore mining	9	Agricultural and sideline product processing	13
Textile industry	17	Food manufacturing	14
Paper manufacturing	22	Beverage manufacturing	15
Petroleum processing	25	Leather and fur products	19
Chemical fiber production	26	Cultural and sports goods	24
Chemical fiber manufacturing	28	Pharmaceutical manufacturing	27
Non-metallic product manufacturing	31	Plastic products	30
Ferrous metal processing	32	Metal products	34
Non-ferrous metal processing	33	Transportation equipment	37
Electric power generation	44	Gas production	45
		Water production	46

Notes: This table documents the classification of industries by pollution intensity, following Jie and Bin (2014). All other industries are categorized as lightly polluting industries.

Table A.4: DID Estimates of the Effect of Environmental Regulations on Industrial Fatalities

Dependent Variable:	Number of Fatalities			
	(1)	(2)	(3)	(4)
Post2014 × Pollution	0.424*	0.424*	0.678***	0.678***
	(0.244)	(0.244)	(0.248)	(0.248)
Year FE	YES	NO	YES	NO
City × Pollution FE	YES	YES	YES	YES
City × Year FE	NO	YES	NO	YES
Observations	5,760	5,760	5,760	5,760
R^2	0.148	0.584	0.155	0.591
Mean Dependent Var.	0.894	0.894	0.894	0.894

Notes: This table reports the DID estimates of the effect of environmental regulations on industrial fatalities. In columns (1) and (2), the treatment group consists of heavily and moderately polluting industries, classified as pollution-intensive, while the control group comprises lightly polluting industries. In columns (3) and (4), the treatment group includes heavily polluting industries, with the control group comprising moderately and lightly polluting industries. Specifications in columns (1) and (3) include year fixed effects and city-by-industry-type fixed effects, and specifications in columns (2) and (4) include city-by-industry-type fixed effects and city-by-year fixed effects. Standard errors in parentheses are clustered at the city level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.5: Poisson Estimates of the Effect of Environmental Regulations on Industrial Accidents

Dependent Variable:	Number of Accidents	
	(1)	(2)
Post2014 × Pollution	0.607***	0.607***
	(0.092)	(0.092)
Year FE	YES	NO
City × Pollution FE	YES	YES
City × Year FE	NO	YES
Observations	5,760	5,760
Mean Dependent Var.	0.285	0.285

Notes: This table reports the Poisson estimates of the effect of environmental regulations on industrial accidents, specifically presenting the coefficient β from Equation (1). The treatment group of this table consists of heavily polluting industries, classified as pollution-intensive, while the control group comprises moderately and lightly polluting industries. The specification in column (1) includes year fixed effects and city-by-industry-type fixed effects, and the specification in column (2) includes city-by-industry-type fixed effects and city-by-year fixed effects. Standard errors in parentheses are clustered at the city level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.6: Negative Binomial Estimates of the Effect of Environmental Regulations on Industrial Accidents

Dependent Variable:	Number of Accidents	
	(1)	(2)
Post2014 × Pollution	0.673***	0.673***
	(0.106)	(0.106)
Year FE	YES	NO
City × Pollution FE	YES	YES
City × Year FE	NO	YES
Observations	5,760	5,760
R^2	0.003	0.003
Mean Dependent Var.	0.285	0.285

Notes: This table reports the negative binomial estimates of the effect of environmental regulations on industrial accidents, specifically presenting the coefficient β from Equation (1). The treatment group of this table consists of heavily polluting industries, classified as pollution-intensive, while the control group comprises moderately and lightly polluting industries. The specification in column (1) includes year fixed effects and city-by-industry-type fixed effects, and the specification in column (2) includes city-by-industry-type fixed effects and city-by-year fixed effects. Standard errors in parentheses are clustered at the city level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.7: The Effect of Environmental Regulations on Ordinary Industrial Accidents

Dependent Variable:	Number of Ordinary Accidents	
	(1)	(2)
Post2014 × Pollution	0.119***	0.119***
	(0.028)	(0.028)
Year FE	YES	NO
City × Pollution FE	YES	YES
City × Year FE	NO	YES
Observations	4,500	4,500
R^2	0.341	0.695
Mean Dependent Var.	0.218	0.218

Notes: This table reports the DID estimates of the effect of environmental regulations on ordinary industrial accidents. Ordinary accidents refer to accidents with no more than three fatalities. The sample includes all industrial accidents in WiseNews that caused no more than three fatalities. The treatment group of this table consists of heavily polluting industries, classified as pollution-intensive, while the control group comprises moderately and lightly polluting industries. The specification in column (1) includes year fixed effects and city-by-industry-type fixed effects, and the specification in column (2) includes city-by-industry-type fixed effects and city-by-year fixed effects. Standard errors in parentheses are clustered at the city level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.8: DID Estimates on Official Dataset

Dependent Variable:	Number of Accidents			
	(1)	(2)	(3)	(4)
Post2014 × Pollution	0.068**	0.068**	0.090***	0.090***
	(0.028)	(0.028)	(0.030)	(0.030)
Year FE	YES	NO	YES	NO
City × Pollution FE	YES	YES	YES	YES
City × Year FE	NO	YES	NO	YES
Observations	6,400	6,400	6,620	6,620
R^2	0.267	0.647	0.320	0.675
Mean Dependent Var.	0.237	0.237	0.337	0.337

Notes: This table reports the DID estimates of the effect of environmental regulations on industrial accidents using the official dataset of SAWS. The sample of columns (1) and (2) includes all industrial accidents documented in official data, and the sample of columns (3) and (4) includes all industrial accidents documented in either WiseNews or SAWS, with the duplicated accidents omitted. The treatment group of this table consists of heavily polluting industries, classified as pollution-intensive, while the control group comprises moderately and lightly polluting industries. The specifications in column (1) and (3) include year fixed effects and city-by-industry-type fixed effects, and the specifications in column (2) and (4) include city-by-industry-type fixed effects and city-by-year fixed effects. Standard errors in parentheses are clustered at the city level. * p<0.1; ** p<0.05; *** p<0.01.

Table A.9: Firm-level Evidence

Dependent Variable:	Indicator of Accidents	
	(1)	(2)
Post2014 × Pollution	0.049***	
	(0.018)	
PostPenalty		0.040*
		(0.023)
Year FE	YES	YES
Firm FE	YES	YES
Observations	12,615	6,241
R^2	0.648	0.652
Mean Dependent Var.	0.683	0.680

Notes: This table reports the DID estimates of the effect of environmental regulations on industrial accidents at the firm level. The sample includes all firms that experienced at least one documented industrial accident in WiseNews and were identifiable from news reports. The dependent variable $CumulativeAccident_{it}$ is an indicator taking the value 1 if firm i has experienced at least one industrial accident prior to or in year t, and 0 otherwise. $PostPenalty_{it}$ is a dummy indicating whether firm i was penalized prior to or in year i. The treatment group of this table consists of firms of heavily polluting industries, and the control group comprises moderately and lightly polluting industries. All specifications include year fixed effects and firm fixed effects. Standard errors in parentheses are clustered at the firm level. Standard errors in parentheses are clustered at the city level. * p<0.1; ** p<0.05; *** p<0.01.