**What is the differential impact of corporate environmental liabilities on the short-term profitability vs. long-term financial outcomes of publicly listed firms in the U.S.? – A Deep Dive across Industries**

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**Abstract**

This study examines the financial impact of corporate environmental liabilities on publicly listed companies in the U.S. It analyses the long-term impact on revenue and EBIT using a fixed-effects panel regression and the short-term impact on stock returns using an event study. The findings reveal a statistically significant negative long-term impact of penalties on revenue, indicating that the financial consequences are driven primarily by reputational damage rather than a direct effect on profitability (as measured by EBIT). No statistically significant short-term impact on stock returns was observed. Furthermore, additional perspectives across different types of violations, industries and company sizes offer further insights into the topic.

*Corporate Environmental Liabilities, Environmental Violation, Violation Tracker, Financial Impact*

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## 1. Introduction

In recent decades, the need to achieve a balance between environmental protection and economic development has gained global attention, and environmental issues such as pollution and natural resource depletion take center stage in corporate decision making (D. Li et al. 2017). Corporations, particularly those with significant environmental footprints, are facing increasing scrutiny from stakeholders, regulators, investors, and consumers, demanding responsible environmental practices (Negash and Lemma 2020). Furthermore, it has become mandatory for companies to include environmental, social and governance (ESG) measurement standards into their reporting (Barman 2018). Regulatory frameworks, such as the European Union's Green Deal and the U.S. Environmental Protection Agency (EPA) regulations, require companies to lower carbon emissions, manage waste appropriately, and adopt sustainable operations (European Commission 2021; Environmental Protection Agency 2024). Non-compliance with regulations can result in significant environmental liabilities including fines, legal settlements, and costly remediation efforts (Environmental Protection Agency 2024). For instance, in 2021, the EPA's enforcement actions resulted in approximately $1,500 million in penalties, stressing the magnitude of penalties issued in only a year (United States Environmental Protection Agency 2022). Among them, companies in the U.S. seem to especially violate the Clean Air Act, resulting in a much higher average count of air pollution violations (approximately 105 per year) compared to other violations averaging around 20 per year. Notably, the company Toyota faced a large fine of $180 million for failing to report air emission-related defects and consequently violating the U.S. Clean Air Act (Gitlin 2024). Logically, such environmental liabilities could have a severe impact on a company, including their financial performance, their corporate reputation or many other aspects (Y. Li, Richardson, and Thornton 1997). However, existing literature on the relationship between paying corporate environmental penalties and the financial performance of companies is limited and reveals inconsistencies in findings. Studies often present divergent findings due to different definitions and methodologies applied in the analyses (Horváthová 2010). For instance, while some studies state a positive impact of environmental regulation and innovation (Clarkson, Overell, and Chapple 2011), others highlight significant short-term financial burdens (Lioui and Sharma 2012; D. Li et al. 2017). Additionally, the current literature does not compare the short-term impact of environmental penalties to a longer term effect on company financials. Furthermore, the matter of environmental penalties has not yet been examined taking other influential factors and characteristics into consideration. Therefore, it is interesting to break down the topic by the most common types of violations, the most frequently violating industries, as well as differentiating companies according to their size.

Overall, companies with a poor environmental performance might experience diminished financial outcomes due to the costs involved of penalties and as society grows more cautious on company activities (Clarkson, Overell, and Chapple 2011). Negative environmental practices could lead to public backlash, damaging a company's brand and eroding long-term customer trust (Bebbington, Larrinaga, and Moneva 2008). Consequently, it seems to be crucial for companies to effectively manage environmental liabilities to maintain organizational stability and a sustainable reputation. This study examines the relationship between corporate environmental liabilities in the form of environmental penalties and their potential impact on the financial performance of public companies in the United States (U.S.). The overarching hypothesis of this study is that there is a differential short-term versus long-term impact. It is assumed that while the short-term effect, which can be observed in an instant around the announcement of a penalty payment, does influence a company's stock price performance, whereas no long-term effect can be discovered. The findings of this study reveal that in the long-term penalties actually seem to be associated with a slight negative effect on revenue, likely due to indirect reputational damage. On the other hand, the impact on financial profitability, measured as EBIT, appears to be negligible. In the short term no actual financial impact can be observed, potentially due to stock prices around the event being influenced by many other external factors. Furthermore, performing deep dives across different violation types, industries, and company sizes reveals that air pollution and hazardous waste violations do reduce top-line performance, while other violation types rather affect the profitability of companies. Also, companies operating in the manufacturing industry as well as smaller companies seem to be particularly vulnerable, whereas companies in other industries or of larger size show greater resilience.

To conduct the analysis, a quantitative research methodology was chosen. To analyze the long-term effect the methodology of a fixed effect panel regression analysis was selected in order to be able to control for multiple companies across many years. To analyze the short-term effect, an event study regression analysis was applied using abnormal returns around the penalty date and comparing them to the historic expected returns. The data for the analyses was gathered from the Violation Tracker – containing information on penalties imposed per company – as well as from the financial database of the Wharton Research Data Services (WRDS). Furthermore, ESG data from Kaggle was added to retrieve more information on the environmental performance of companies. Additionally, event study data containing stock returns around the penalty dates was retrieved using the WRDS event study system. In the analysis, data between 2000 and 2022 was considered, since for all years following no sufficient financial information can be retrieved.

This paper is structured into six chapters. This first chapter sets the background to the study and gives reasoning to why researching the impact of corporate environmental violations on financial performance is insightful. In chapter two, a literature review conceptualizes the theory of corporate environmental liabilities and defines how such will be considered in the context of this study. Then, the development and current landscape of environmental regulations will be reviewed and context for later deep dives into different types of violations, violations across industries as well as different company sizes will be given. Consecutively, gaps in current literature are identified and will shed some light on the relevance of this study. Chapter three starts by outlining the data cleaning and merging process, ensuring the dataset is properly prepared and aligned for subsequent analysis. Furthermore, a detailed explanation of the study's methodology is provided, including the rationale for selecting a fixed-effect panel regression analysis and an event study regression. In chapter four, first a comprehensive and descriptive overview of the entire data is provided. Then, the results from both regression analyses on the entire sample are presented and interpreted. Subsequently, chapter five will focus on differences in the results across the above-mentioned deep-dives, increasing the depth and thoroughness of this study and proving the high relevance of other factors in the context of this analysis. Finally, chapter six will conclude the study and suggests applicable recommendations as well as potential opportunities for further research within this subject.

## 2. Literature Review

This chapter discusses the theoretical background of corporate environmental liabilities and reviews the current state of academic research on this topic. First, the concept of corporate environmental liabilities will be clearly defined. Next, the historical development of the environmental regulatory framework in the U.S. and the current regulatory landscape is laid out. The following section examines existing literature on whether corporate environmental liabilities have an impact on companies' financial performance. Finally, the last three sub-chapters will give context to why it is insightful to perform the later deep-dives across specific kinds of violation, different industries as well as companies of different size.

### 2.1 Conceptualization of Corporate Environmental Liabilities (CEL)

The concept of corporate environmental liabilities originally is based on the expectations that arise with a general corporate social responsibility (CSR) (Carroll 1991). CSR refers to the obligation of businesses to operate in a way that benefits society and the environment, rather than singularly focusing on profit. A key aspect of CSR is environmental responsibility, where companies are expected to minimize their negative impact on the environment by following certain laws, and thereby reducing pollution and managing resources sustainably (Freeman 2010). Failing to meet such environmental expectations sets the stone for corporate environmental liabilities, which could be either financial or legal consequences that companies face under violation (Carroll 1991). These liabilities can take various forms, including monetary fines or penalties imposed on the company by regulatory bodies, compliance costs associated with meeting environmental standards, compensation obligations due to environmental damage, or damages awarded in lawsuits (Corporate Finance Institute 2024). A company could face fines for exceeding emission limits or a compensation payment due to environmental damage in certain regions caused by hazardous waste spills. By failing to integrate environmental considerations into their operations, companies expose themselves to financials risks, which in turn can affect their profitability or reputation. Therefore, from a company point of view, environmental responsibility is not only an ethical obligation but in principle a strategic consideration (Gabel and Sinclair-Desgagné 1993).

### 2.2 Development of Environmental Regulatory Landscape in the U.S.

The historical development of modern U.S. environmental regulations and policies can be traced back to a few critical milestones that laid the groundwork for current corporate environmental accountability. Herein, the National Environmental Policy Act (NEPA), which was published in 1969, can be viewed as the foundational statute. It required federal agencies to assess the environmental impact of their actions, thereby holding public as well as private companies accountable for environmental harm resulting from their business practices (Anderson 2013). As NEPA was directed at federal agencies instead of corporations, its impact on the American corporate environment was indirect and therefore limited. Nevertheless, it proposed a first official regulatory framework, raising overall public awareness on the need of environmental reporting and disclosure (Bagby, Murray, and Andrews 1995). Building up on NEPA, the Clear Air Act (CAA) and the Clean Water Act (CWA) were introduced in the years 1970 and 1972 respectively (Melnick 2010; Downing, Winer, and Wood 2003). The new acts were a direct response to many environmental crises that showcased the consequences of an unregulated industry. The regulations presented a shift towards a more proactive environmental management, where non-compliance of corporations resulted in legal actions and substantial fines, which consequently posed a critical financial risk to businesses (Bagby, Murray, and Andrews 1995). While above regulations were established to regulate environmental issues concerning air and water pollution, the consecutively introduced Resource Conservation and Recovery Act (RCRA) of 1976 further expanded corporate environmental responsibility by regulating the disposal of hazardous waste (Kovacs and Klucsik 1976). Following these developments, in the 1980 the Comprehensive Environmental Response, Compensation, and

Liability Act (CERCLA) was established. This act, which was also called “Superfund”, imposed a tax on the chemical and petroleum industries that was automatically paid into a trust fund for cleaning up abandoned hazardous waste sites (Barr 1990). Overall, the most pivotal moment that supported the governance of environmental regulation compliance was the establishment of the United States Environmental Protection Agency (EPA) in 1970. The EPA became the central authority responsible for enforcing regulations mentioned above, such as the CAA and the CWA and other regulations (Messer, Linthurst, and Overton 1991). To support the overall awareness, these agencies provide public access to databases containing information of firm’s compliance, making transparency an integral part of the regulatory landscape (Cohen 1998). EPA enforcement actions, such as fines and litigations, have significantly increased the financial and reputational risk of firms that fail to comply with required standards, intensifying corporate accountability in the U.S. environmental domain.

The current regulatory framework in the U.S. builds upon the above-mentioned historical developments and can be considered as very comprehensive measure to ensure corporate accountability (Heitz, Wang, and Wang 2023). To give context to the specific environmental regulations holding companies accountable, this section describes the most relevant in more detail. The CWA is an important regulation with the goal to restore and maintain water quality by regulating the discharge of pollutants into surface waters such as rivers, lakes and streams. One part of it includes the implementation of pollution control like setting wastewater standards for industries. Furthermore the act prohibits the discharge of pollutants from a point source into navigable waters without a permit, which is regulated by the EPA's National Pollutant Discharge Elimination System (NPDES) (United States Environmental Protection Agency 2024). The CAA on the other hand regulates air emissions and authorizes the EPA to set National Ambient Air Quality Standards (NAAQS) to protect public health and welfare. Achieving the NAAQS was one of the main goals of this act. The Act also mandates State

Implementation Plans to meet these standards and requires the EPA to regulate hazardous air pollutants through maximum achievable control technologies for major sources of pollution (United States Environmental Protection Agency 2024). The RCRA is a law that takes care of hazardous and non-hazardous solid waste. Its main goal is to protect the environment and human health, conserve natural resources and reduce waste. Therefore it created a framework for right handling, storage, treatment and disposal of waste, with a particular focus on hazardous waste (United States Environmental Protection Agency 2024). Lastly, CERCLA was enacted to handle the release of hazardous waste that may be dangerous for the environment and public health. It imposes a tax on the chemical and petroleum industries, which is invested in a trust fund for the cleanup of abandoned or uncontrolled hazardous waste sites. (United States Environmental Protection Agency 2024).

### 2.3 Impact of Corporate Environmental Liabilities on Financial Performance

The financial performance of a firm is of great importance for stakeholders, investors and the overall economy. To assess good financial performance, several indicators are commonly used stemming from many studies and frameworks. Common measurements to assess financial performance are profitability and liquidity ratios, growth indicators or the cash flow of a company. A well-performing company can deliver higher dividends, share price appreciation, and overall a better profitability among others (Mirza 2013). Additionally, a financially successful business enhances employee income, provides higher quality products to consumers, and is better positioned to adopt environmentally friendly production practices (Mirza 2013). Reviewing current literature on the financial performance, numerous factors have been identified that can generally have either a positive or negative effect on final company results (Clarkson et al. 2011).

For instance, a meta-regression analysis of 64 outcomes from 37 empirical studies showed, that the impact of environmental regulations on financial performance is complex and varies depending on numerous factors like the type of legal system, the time coverage or the kind of empirical method conducted (Horváthová 2010). Several of the papers considered in this meta-regression analysis argue that regulations can positively impact a firms' financial performance by driving innovation and encouraging companies to develop new and more efficient technologies. Conversely, some empirical studies point to a short-term negative relationship, often attributed to factors such as pollution control and environmental improvements, which tend to yield diminishing marginal net benefits over time. Furthermore, the analysis shows that a negative relationship between environmental and financial performance increases when simple correlation coefficients are used instead of more advanced econometric methods or when portfolio studies are conducted, likely due to the omission of important influencing factors in their analyses.

Additionally, evidence from a study covering 478 events from 1980 to 2000 highlights the immediate financial consequences of environmental violations (Karpoff, Lott, Jr., and Wehrly 2005). Firms investigated or accused of violating environmental regulations saw statistically significant and economically substantial short-term declines in common share values, with abnormal stock returns dropping by -1.69% following violation announcements. This empirical evidence demonstrates that news of environmental violations corresponds directly to shareholder losses, indicating the severe market repercussions of regulatory non-compliance for a small sample between 1980 to 2000 (Karpoff, Lott, Jr., and Wehrly 2005).

Overall, companies with stronger financial resources and advanced management capabilities are better positioned to invest in sustainability initiatives and leverage their strategic advantages for environmental innovation. According to a recent study, proactive corporate environmental policies leading to less environmental liabilities, might be indeed interrelated with financial success (Clarkson et al. 2011). This study models the causal link between a firm's environmental performance and their financial resources. Improvements in environmental performance were shown to enhance financial performance, indicating that effectively managing environmental liabilities could increase financial returns. The study concludes that the positive link between environmental and financial performance is robust, giving firms that adopt green strategies a competitive advantage, though such strategies are not easily replicated by all companies (Clarkson et al. 2011).

However, it can be assumed that not all companies equally benefit from more proactively engaging in environmental practices. The positive effect of corporate environmental responsibility on the financial performance of the firms is often questioned due to the substantial upfront investments that businesses are required to make (Li et al. 2017). Zhao and Murrell (2016) reveal that corporate environmental performance does not always positively affect corporate financial performance, emphasizing the complexity of the relationship between the two (Zhao and Murrell 2016). Reviewing the long-term financial performance, engaging in environmental corporate social responsibility (ECSR) negatively affects firms' ROA. The median ROA stands at 4%, but firms that focus on ECSR strengths see a reduction of 0.8%, while those having ECSR concerns experience a decrease of 0.6%. Hence this is showing that nearly a quarter of the median ROA is absorbed by ECSR activities, highlighting the financial burden of ECSR initiatives (Lioui and Sharma 2012).

### 2.4 Implications of Environmental Violations by Type

Analyzing environmental violations without considering their specific types may cause significant differences in their financial implications. Different violation types - such as air pollution, water pollution, and hazardous waste violations- are subject to distinct regulatory penalties (see chapter 2.2), remediation costs, and levels of public concern. For instance, air pollution violations, often linked to climate change, can lead to substantial reputational damage due to heightened media scrutiny and public awareness (Konar and Cohen 1997). In contrast, hazardous waste violations may result in higher cleanup costs and legal liabilities because of their potential for long-term environmental and health impacts (Hamilton 1995). Additionally, the extent of the monetary penalty amount as well as the frequency might differ across different kinds of violations. Therefore, a disaggregated analysis is essential to accurately understand the unique financial effects associated with each violation type, enabling more targeted corporate strategies and policy interventions.

### 2.5 Industry Implications of Environmental Regulations

Recent literature highlights that the impact of environmental regulations varies significantly across industries. It becomes evident that this can be primarily attributed to differences in key factors such as pollution intensity, or the regulatory burden of specific industries. Industries that are highly pollution-intensive, such as manufacturing, energy, and chemicals, tend to face stricter regulatory oversight and higher overall compliance costs (Gray and Shadbegian 2003). Conversely, industries with lower pollution profiles, such as technology or finance, typically experience fewer regulatory burdens (Ambec et al. 2013). Subsequently, it could be assumed that the impact that such environmental regulations have on specific companies might vary across different industries. For instance, research on the motor vehicle industry has demonstrated that stringent environmental regulations significantly influence where companies choose to operate, as they seek regions with more lenient regulatory frameworks to minimize compliance costs and maximize profitability (McConnell and Schwab 1990). Similarly, studies analyzing the effects of air quality regulations reveal that polluting industries, especially those with high emissions such as manufacturing or energy sectors, are more sensitive to local regulatory environments (Becker and Henderson 2000). Furthermore, some studies state that higher pollution industries actually face significantly higher compliance costs, potentially affecting their financial performance to a larger extent than other industries (Gollop and Roberts 1983; Gray and Shadbegian 2003).

## 2.6 Implications of Company Characteristics on Environmental Performance

Generally, company characteristics such as a company's ownership structure, corporate governance practices, the size of a company or its financial leverage can have an impact on the environmental practices of a company (Darnall, Henriques, and Sadorsky 2010). First of all, the ownership structure of companies affects how they respond to environmental liabilities, since publicly listed companies face greater pressure from shareholders and regulatory bodies, which increases the impact of environmental violations on stock performance for instance (Sharfman and Fernando 2008). In contrast, private companies might experience less public scrutiny but could be more adversely affected by financial penalties due to limited access to capital markets (Delmas and Toffel 2008). Furthermore, corporate governance practices are crucial in managing environmental risks, as robust governance structures enable firms to better identify and mitigate such risks (Berrone et al. 2013). Eeffective governance promotes transparency and accountability which could help mitigate damage resulting from environmental incidents (Russo and Fouts 1997). Next, also the financial leverage influences a firm's ability to absorb costs associated with environmental penalties. Highly leveraged companies have less financial flexibility, making it more challenging to address financial burdens related to environmental penalties (Sharfman and Fernando 2008). Last, the size of a company affects its capacity to effectively manage environmental liabilities and regulatory requirements. Larger firms are typically better equipped to invest in advanced environmental technologies and compliance programs, which cand reduce the frequency and especially severity of violations (Darnall, Henriques, and Sadorsky 2010). This resource advantage may protect them against the negative financial impacts of penalties, whereas smaller companies might lack such resources, making them more prone to financial damage resulting from environmental liabilities (Sharfman and Fernando 2008).

In addition to general company characteristics, firms recognize that strong ESG performance, reflected in ESG scores, is crucial for sustained success. High scores indicate a focus on long-term shareholder value over short-term gains (Tarmuji, Maelah, and Tarmuji 2016). There are different well known ESG ratings, like Bloomberg, Morgan Stanley Capital International (MSCI) and Thomson Reuters. They all aim to provide transparent and objective measures of a company's relative ESG performance, commitment and effectiveness. Usually, companies get assigned letter grades or a specific score representing their performance over the years. For example, Thomson Reuters evaluates a subset of 178 key ESG measures across 10 categories including among others: the use of resources, company emissions, social factors like workforce management and human rights, and governance aspects including management, shareholders, and CSR strategy using company-reported information (Thomson Reuters 2018).

### 2.7 Gaps in Current Literature

Several papers have described the relationship between environmental responsibility and financial performance, with somewhat different results. Although empirical studies have demonstrated a significant relationship between corporate environmental performance and financial success, the evidence remains inconsistent regarding whether a reduction in environmental liabilities consistently improves a firm's financial performance (Clarkson et al. 2011). The variation in existing studies can be attributed to several factors. Many studies suffer from limitations such as small sample sizes, the absence of standardized environmental criteria, and differences in firm size or geographic location. Additionally, some studies fail to account for key variables that influence profitability. These inconsistencies are often driven by methodological differences and unclear definitions of both financial and environmental metrics, which lead to inconclusive results across studies (Horváthová 2010). Furthermore, current literature does also not specify a differential impact of a short-term versus long-term effect of the liabilities on financials. Additionally, most studies treat environmental violations as a homogenous category, neglecting the unique impact that specific types of violations might have. Disaggregating CELs by type could increase the understanding of the topic and help to identify the most impactful violation types. The same can be stated for the different industries in which companies that are being fined operate in. High-pollution industries, such as manufacturing or energy, face more stringent regulations and could therefore have a much different relevance in the context of environmental violations. Understanding how CELs impact companies across different industries enables a more tailored analysis and could increase effectiveness in the future.

# 3 Methodology

This chapter will elaborate on the methodology employed in this study. First, the data collection process will be outlined, followed by a detailed explanation of the merging procedure. A testing phase was conducted on the final merged dataset to ensure its reliability and accuracy; details of this process can be found in Appendix A. Then, the research design will be explained, and the scope of the study will be narrowed down. In the following step, the statistical methods chosen will be explained in more detail.

## 3.1 Data Collection and Cleaning

The data for this study was gathered from multiple sources, including the Compustat database of the Wharton Research Data Services (WRDS), as well as Violation Tracker (VT) and finally Kaggle. The Stata code used for this analysis is available as supplementary material accompanying this study.

To account for the environmental liabilities a dataset from Violation Tracker (VT) has been taken into consideration. The VT is a comprehensive database that aggregates information on corporate misconduct across the U.S., detailing violations and penalties incurred by businesses in various industries. The platform serves as a vital resource, promoting transparency and accountability in corporate behavior (Good Jobs First 2024). The dataset comprises companies headquartered in 56 different countries, with over 78% of the violations conducted from companies headquartered in the U.S. In total it contains 655,200 violations from 1$^{st}$ of January 2000 until the 27$^{th}$ of September 2024 and 50 different variables specifying the type and exact reporting date of violation among others. Moreover, the Violation Tracker reports violations for publicly listed as well as private companies. This analysis is limited to the observations with headquarter in the U.S. (552,469 observations dropped) and the years between 2000 and 2022, and therefore all observations from the beginning of the year 2023 onwards are removed (6,660 observations dropped). The dataset contains various types of violations beyond environmental violations (Table 1), which is why only the relevant violations (environmental-related offenses) will be retained (79,444 observations dropped).

**Table 1:Overview of Offense Groups in the United States (2000 – 2022)**

| | Freq. | Percent | Cum. |
|---|---|---|---|
| Competition-related Offenses | 1,099 | 1.144 | 1.144 |
| Consumer-protection-related Offenses | 7,144 | 7.436 | 8.580 |
| Employment-related Offenses | 9,360 | 9.743 | 18.323 |
| Environment-related Offenses | 16,627 | 17.307 | 35.630 |
| Financial Offenses | 2,156 | 2.244 | 37.874 |
| Government-contracting-related Offenses | 1,258 | 1.309 | 39.184 |
| Healthcare-related Offenses | 8,421 | 8.765 | 47.949 |
| Miscellaneous Offenses | 28 | 0.029 | 47.978 |
| Safety-related Offenses | 49,978 | 52.022 | 100 |
| **Total observations** | **96,071** | **100** | |

*Note. – Data collected from the Violation Tracker in 2024.*

Subsequently, all relevant variables are retained including: “penalty_year”, “penalty_date”, “current_parent_name”, penalty_adjusted”, “primary_offense”, “current_parent_stock_ticker”, and “reporting_date_parent”. Following this, some variables were renamed in order to facilitate the merge later. Then, the ticker and year needed to be cleaned and formatted correctly and tickers without any value or zero are removed from the dataset (4,182 observations dropped). Last, all observations with an empty penalty amount are dropped since they are not relevant to this study (359 observations dropped). The following table gives an overview of the descriptive statistics of the penalty amount (Table 2).

**Table 2: Summary Statistics of Penalty Amount**

| | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Penalty Amount | 12,086 | 3,255.876 | 72,000 | 0.408 | 5,150,000 |

*Note. – Data collected from the Violation Tracker in 2024 in thousand USD ($0,000).*

To account for the companies which have switched their parent company after the violation occurred, a second dataset from VT is taken into consideration. This dataset contains 3,087 observations and 4 variables including the parent company during the violation announcement, the historical ticker of this parent company, the central index key (CIK) and the international security identification number (ISIN). The location of the reporting date company is generated from the ISIN data, retaining only U.S.-based companies (956 observations dropped). Additionally, the ticker variable is adjusted and cleaned again and only the historical ticker and reporting date company information are kept for subsequent merging.

Firm-specific financial data is provided by the data platform powered by the WRDS, which grants academic and professional users access to a comprehensive collection of financial information. Compustat Fundamentals, accessible through WRDS, delivers standardized financial statements and market data for more than 80,000 active and inactive publicly traded companies across North America (and a few other countries), serving as a trusted resource for financial professionals for half a decade (Wharton Research Data 2024a). For the purpose of this study two separate datasets with data from the year 2000 up until 2022 were downloaded from WRDS. The first dataset contains 220,777 unique entries, already filtered for Northern American companies only, including 15 variables such as the year, ticker, parent company name and various annual financials (Earnings before interest and taxes (EBIT), total revenue, etc.). For further analysis, only essential data was retained from this dataset. Therefore, entries without a ticker (private companies) or without a year have been removed (93 observations dropped). Furthermore, to be coherent all rows with a year entry below the year 2000 were removed (1,394 observations dropped). Finally, the variable "comn" was renamed to "parentcompany" to ensure consistency with the other datasets and only the columns for the year, ticker, parent company, revenue, asset value, and EBIT were preserved.

Following the same procedure, several financial ratios for firms in Northern America have been downloaded from WRDS. The platform provides access to more than 70 pre-calculated financial ratios, organized into eight main categories, including valuation, liquidity, and profitability, among others (Wharton Research Data 2024b). Users have the option to obtain both firm-level and industry-level ratios through a simple point-and-click interface in the web query. In the context of this study, only firm-level ratios have been selected. This second dataset includes 11 variables and a total of 1,159,868 observations. Several cleaning steps are required to prepare the data for merging with other datasets. Since year and ticker will be used as merging keys later, a new column for the year was created by extracting the first four characters from the "public_date" variable and storing them in a year column. All rows without an entry for year and ticker needed to be dropped (26,418 observations dropped). As later explained in chapter 3.1 the financial data from these two datasets will be used as key indicators for the financial performance of companies in the analysis.

The next dataset that was retrieved is a CSV file containing public company ESG ratings from Kaggle (Kaggle 2024). This dataset contains ESG scores and ratings for 722 publicly traded companies across various industries in Northern America. Each row in the dataset represents a single company and key columns include basic company information, environmental, social, and governance scores, as well as overall ESG ratings. ESG performance is assessed using numerical scores (where a higher score indicates better performance), letter grades (e.g., AAA), and categorical levels (e.g., High, Medium, Low). This setup enables analysis of ESG distribution across industries and its relationship with financial metrics like profitability and stock returns. Similar to the previous dataset, the ticker names in this dataset have been cleaned, and only the essential columns relevant to this study - namely ticker, company name, total level, and total grade - have been retained.

For the subsequent event study, a tool from WRDS is used. A file containing the tickers and event dates for all violations in the dataset, is prepared and uploaded. This file is created by extracting relevant information from the merged dataset, as explained in chapter 3.2. The tool generates a new file with the abnormal returns for each event day. After excluding missing abnormal return values (942 observations dropped), the average abnormal returns ("mean_aret") and cumulative abnormal returns ("car") are calculated for each combination of ticker and event date. Duplicates are then removed to retain only one record per event (16,245 observations dropped). Finally, the variable names are adjusted to align with the merging process for the violation dataset and stock returns used in the short-term analysis.

### 3.2 Data Merging Process

The integration of different datasets is a crucial step in this study, as it allows for a comprehensive analysis of financial performance, environmental violations, and ESG ratings. Initially, the cleaned fundamental financial dataset from Compustat was loaded. In this dataset, financial metrics such as revenues, total assets and EBIT were aggregated by year and ticker symbol. This aggregation involved calculating total revenues and assets to ensure that the data reflected the consolidated financial performance of parent companies on a yearly basis. Then, duplicates were identified and removed (11 observations dropped).

Next, the consolidated dataset is combined with the dataset from WRDS containing monthly financial ratios. To prepare this data for annual analysis, the yearly averages of each ratio for every company were calculated. To ensure each company-year combination is unique, all duplicate entries based on the ticker and year variables were removed, resulting in the deletion of 1,031,303 redundant observations. Next, columns with monthly ratio variables were excluded from the dataset, as only annual ratios are required for further analysis. Finally, the variables are renamed to ensure consistency across all datasets. The final datasets are then merged one-to-one, utilizing the common identifiers of ticker symbol and year. Any records from the file containing financial ratios, which couldn't be merged to financial fundamentals, were discarded to maintain the integrity of the dataset (33,838 observations dropped). In this step it is ensured that all companies that might have reported on financial ratios, but no record on financial fundamentals such as revenue, are discarded from the dataset.

Before integrating the VT into the financial dataset, the two VT datasets need to be merged for a comprehensive analysis. To begin, the cleaned VT data is merged with the historical ticker data based on the reporting date, linking each company with its ticker on the announcement date of the violation (m:1 merge). Historical tickers without a corresponding reporting-date-parent company in the Violation Tracker file are removed to retain only entities, which can be useful for further analysis (1,198 observations dropped). A new ticker variable is created to reflect changes: if the parent company differs from the reporting-date parent, the variable switches to the historical ticker; otherwise, it retains the ticker from the basic cleaned file. Finally, records with missing tickers are dropped, the new ticker variable is renamed, and the dataset is saved for further analysis (1,429 observations dropped).

Subsequently, the adjusted VT dataset was integrated into the financial dataset that resulted from the previous two steps. In this step a many-to-one merge was performed using the ticker and year as identifiers. Since there can be multiple violations in the same year for the same ticker, a one-to-one merge is not possible. The merge results in the inclusion of all environmental violation data and links them to the respective parent company and year in the financial dataset. As a result of the merge, only the violations with merged financials are kept in the merged dataset (215,900 observations dropped).

Finally, the ESG ratings dataset was merged with the latest dataset containing financials as well as violation data using a many-to-one merge. Consequently, only those entities of the ESG ratings data that have a matching ticker symbol in the master data are retained, since all other companies will be irrelevant in the analysis (461 observations dropped).

Afterwards variables for revenue, EBIT, penalty amount, and assets are adjusted to ensure consistent monetary units, making them comparable across observations. In addition, the penalty amount variable is standardized by dividing it by the asset variable to make it comparable across all companies in the dataset. For the main analyses in this study only the standardized penalty (after this paragraph referred to as penalty) is considered to be able to compare easily across companies. Considering this, the original variable for the penalty amount will be referred to as penalty non standardized. Table 3 below shows both the non-standardized and standardized penalty amounts, with the standardized penalty amount in percentage. The number of observations for the non-standardized penalty amount is lower compared to Table 2 above, as observations without any financial data were excluded. In addition, the standardized penalty amount includes 38 fewer observations than the non-standardized amount. This discrepancy results from the fact that although financial data is available for certain observations, the corresponding asset values required for standardization were missing.

**Table 3: Summary Statistics of Penalty Amount (non-) standardized**

| | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Penalty non-standardized | 9,579 | 3,402.907 | 78,623.618 | 0.408 | 5,150,000 |
| Penalty standardized | 9,541 | 0.000 | 0.006 | 0.000 | 0.366 |

*Note. – Data collected from WDRS in 2024. Penalty non-standardized in thousand USD ($0,000) and Penalty standardized in Percentage (%).*

For the short-term analysis later, the above-described dataset will be further combined with the event study dataset. The penalty amounts are aggregated by penalty date for every company, consolidating multiple penalty amounts on the same date, and duplicate entries based on “tic” and “penalty_date” are removed (539 observations dropped). Afterwards the penalty date is reformatted. The dataset is merged with the stock price data on a one-to-one basis using “penalty_date” and “tic” as key variables. Only entries with stock price data are kept (1,388 observations dropped).

### 3.3 Research Design

As addressed in the previous chapter, the implications of environmental regulations can have a substantial impact on the performance of companies on several dimensions. Additionally, the awareness of the environmental impact that corporations have has risen immensely lately, which additionally puts pressure on companies to adhere to regulations. While some studies have proven that environmental regulations in fact do influence the selection of company location for instance, there is still a gap in academic research which examines the impact that such regulations could have on the short- and long-term financial performance. The general consequence of a company breaching an environmental regulation is a corporate environmental liability, which can include many forms of fine payments and other penalties (see chapter 2.1). Logically, one would assume that such payments have at least a short-term effect on the financial performance of companies. On the other hand, contradictory the long-term effect of corporate environmental liabilities might be less strong or even not existing. This study aims to determine if such assumptions can be proven by answering the following research question:

*What is the differential impact of corporate environmental liabilities on the short-term profitability vs. long-term financial outcomes of publicly listed firms in the U.S.?*

To be able to make a comparison between the long-term effect and the short-term effect of corporate environmental liabilities, this study will focus on answering two specific hypotheses. First, since penalty amounts are rather small compared to the turnover of publicly listed companies, it is assumed that on the long-term the effect of paying a penalty on the financial performance of companies is rather small. For instance, in 2016 Apple paid a penalty of $450,000 compared to a year-end revenue of approximately $216 billion, implying that the penalty comprised 0.0002% of Apple's turnover. Concludingly, the hypothesis is the following:

*H0(1): There is no long-term effect of corporate environmental liabilities on the financial performance of publicly listed companies in the U.S.*

On the other hand, looking at the short-term effect of corporate environmental liabilities on the financial performance one could assume that there is a noticeable effect. A publicly listed company that has violated an environmental regulation will most probably end up in the news, and consequently it could be assumed that short-term indicators of financial performance – such as the company's stock price – will suffer from that. For example, the company Boeing had to pay a very large fine of around $40 million on the 14th of May in 2014, and comparing the stock price of that day with the stock price one day after, it can be observed that it dropped from $180.76 on the 14th to $176.99 on the 15th. Therefore, the second hypothesis is the following:

*H0(2): There is a short-term effect of corporate environmental liabilities on the financial performance of publicly listed companies in the U.S.*

To examine the hypothesis described above, a quantitative research methodology was chosen. Such methodology enables to test a broader theory using a data-driven, deductive approach and concludingly analyse observations to either confirm or not confirm a theory. Given the above mentioned research question, this study aims to test the theory of an interdependence between the extend of corporate environmental liabilities and the financial performance of companies. As a result, it will be possible to get an understanding of the effectiveness of the consequences that companies face upon a breach of environmental regulations. Concludingly, it can offer guidance to authorities in charge of corporate environmental liabilities in their decision whether consequences must be more severe or not.

Furthermore, this topic is not only insightful to analyse from a general, but also from a more granular point of view. Therefore, it was chosen to further break down the research topic and investigate whether the impact differs across companies of different sizes, within different industries or dependent on the specific environmental regulation that is considered. To analyse this, this research will incorporate deep dives regarding the following items:

*Deep Dive 1: Impact across violation types*

*Deep Dive 2: Impact across different industries*

*Deep Dive 3: Impact across different company sizes*

Before describing the method of analysis chosen, it is crucial to note that the scope of this research is limited. To maintain a good overview, the study only takes a few key indicators of financial performance into account: the revenue and EBIT from companies income statements, the asset amount from the balance sheet, as well as several financial ratios such as return on equity (ROE), return on assets (ROA), gross profit margin (GPM), net profit margin (NPM), the debt to equity ratio (DE) and the debt to asset ratio (DA). Additionally, since the financial performance of private companies is hardly measurable, such companies are excluded.

For this study, two primary statistical methods are adopted to address the hypotheses: a fixed effect panel regression analysis and an event study regression analysis using abnormal returns. The fixed effect panel regression is particularly suitable for analyzing the long-term effects of corporate environmental liabilities on financial performance because it controls for time-invariant characteristics unique to each company, which might otherwise confound the results. This method has been extensively used in finance and economics research to assess longitudinal relationships and isolate the impact of specific variables over time (Baltagi 2008). In contrast, to assess the short-term impact of environmental liabilities, this study employs an event study methodology. Event studies are highly effective in isolating the immediate market response to specific events, such as regulatory fines, by measuring abnormal returns, or the differences between actual stock returns and expected market returns, around the event date (MacKinlay 1997). This approach is commonly applied in finance research to capture market reactions to unexpected events and allows to estimate the immediate effect of an event on stock prices.

### 3.4 Fixed Effect Panel Regression

As previously discussed, a fixed-effect panel regression was employed to show whether corporate environmental liabilities have a long-term impact on the financial performance of publicly listed companies in the U.S. The collected data (see chapter 3.1) is organized as panel data, a two-dimensional structure that combines a time dimension year (time series) with a cross-sectional dimension (financial data and penalty amount). This format provides richer information for the study and has the advantage of being robust to certain violations of the Gauss-Markov assumptions, such as heteroskedasticity and non-normality (Raharjo 2014). Further this model allows for individuality along the ticker by accepting each to have its own intercept, which is considered time-invariant (Khalil, Khalil, and Khalil 2024). In time series data, one or more variables are observed for a single unit over a certain time period. In contrast, cross-sectional data involves observing multiple units at a single point in time (Zulfikar 2018). Fixed-effects model panel data using a dummy variable technique to reflect the differences between intercept tickers. The regression equation for the fixed-effect model panel data is as follows:

$$(1)\ y_{it} = \alpha_i + \beta X_{it} + \epsilon_{it}$$

With $i \in [1,..,\mathrm{N}]$, N being the tickers; $\mathrm{t} \in [2000,\ldots,2022]$ representing the years; $\alpha_i$ is the intercept specific to each unit (fixed effect); $X_{it}$ representing the set of independent variables, $\beta$ the coefficienet for the independent variables and $\epsilon_{it}$ the error term (Wooldridge 2010).

### 3.5 Event Study Regression

To examine the short-term effect of penalties on financial performance, an event study analysis was conducted. This method examines whether certain events such as earnings announcements or stock splits lead to abnormal returns for shareholders. Abnormal returns are defined as the deviation of observed returns from expected returns based on a selected model (Peterson 1989).

For this study, the relevant event is the day on which the penalty to a company was announced. Afterwards the event window and the estimation window must be determined. The event window refers to the period in which the impact of a particular event on share prices is analyzed. It usually extends over several days before and after the event and records the observed returns during this period (Peterson 1989). In this context, an event window of one day before and one day after the event is used as it captures the immediate market reaction while minimizing noise from unrelated factors. The estimation window is the period before the event that is used to calculate the expected return on the share price that would have been expected without any event. This window generally spans between 100 to 300 days for daily studies (Peterson 1989). In this analysis, the estimation window was chosen to end ten days before the event to avoid possible contamination from information leaks or early market reactions. The estimation window was set to 200 trading days to ensure robust and reliable parameter estimation. There are three main techniques for estimating normal or expected stock returns: the market model, the mean-adjusted model and the market-adjusted model (Peterson 1989). For this analysis the market model is applied. It is well suited for this analysis as it provides a robust framework for estimating expected returns by taking into account the relationship between a company's shares and the overall market. The standardization of abnormal returns improves the accurate testing of hypotheses about market reactions, as it takes into account statistical errors in the calculation of the expected return (Peterson 1989). For this study it is not possible to standardize the return variable as the website used provides neither the returns of the estimation window required to calculate the standard deviations nor directly pre-standardized returns.

# 4 Results and Analysis

In this chapter the results of the study are described and discussed. Consequently, an indication will be given on whether there can be found a long-term or short-term impact of corporate environmental liabilities on the financial performance of companies in the U.S. First, the final dataset will be described. Next, the results of the fixed-panel regression analysis researching the long-term effect on company financials will be examined. Finally, the event study regression analysis with abnormal returns, which examines the short-term effects, is carried out and its results are compared with those of the long-term analysis.

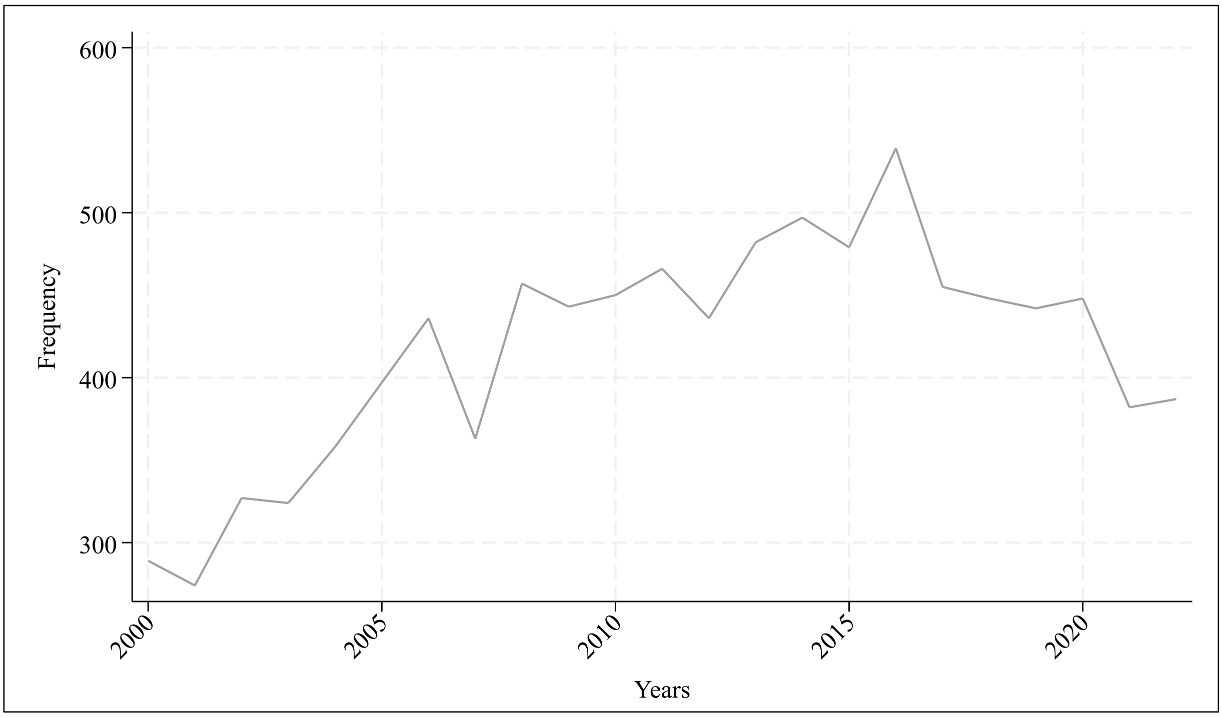
## 4.1 Descriptive Statistics

The long-term dataset is comprised out of four separate sub-datasets the fundamental financials, the financial ratios, the data on violations, and ESG data. This dataset is appropriate to use for descriptive statistical analysis since it has not been collapsed or summarized by year or penalty date yet. Consequently, this data can give a comprehensive overview on how penalties are distributed, what type of penalties exist, across which industries penalties occur the most, and other relevant information. Overall, the data contains 9,579 total observations and 41 different variables (see Appendix F). Furthermore, variables are stored in different data types including string variables, long variables, and float variables. Moreover, the data contains information for the years from 2000 to 2022 and only entails companies that are headquartered in the U.S., since data after 2022 and companies outside the U.S. has been excluded earlier. Within the U.S., the data contains 814 distinct companies.

### Penalty Count & Amount

To understand the trends in corporate penalties over time, the analysis focuses on the frequency of penalty events and the financial penalty amounts over the study period. First, the total penalty count was cumulated per year (Figure 1). The results show that the frequency of violations steadily increased from 2000 to a peak in 2016 with a count of 539 violations, followed by a notable decline in the subsequent years. This could be caused by potentially reflecting changes in regulatory enforcement, corporate behavior, or reporting practices.

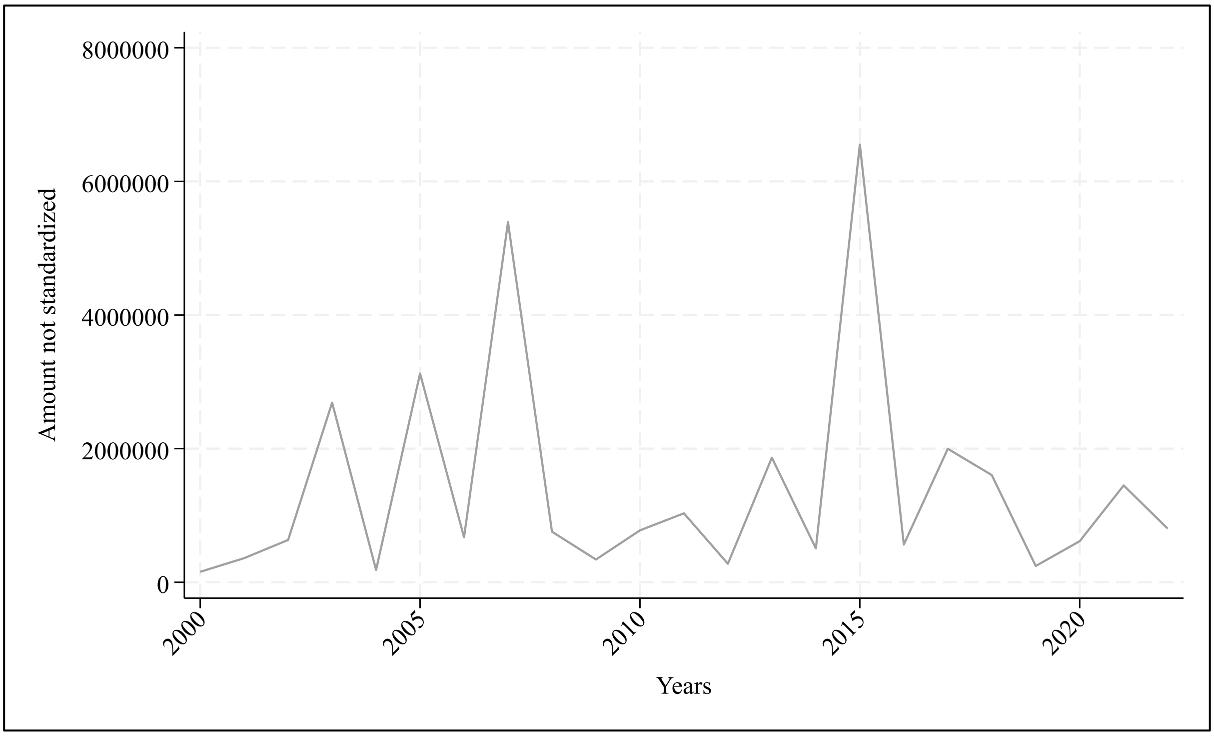
**Figure 1: Total Violation Frequency between 2000 and 2022**




*Note. – Data collected from the Violation Tracker in 2024.*

The penalty amounts demonstrate significant variation over the years, starting with a minimum of $156.2673 million in 2000 (Figure 2). Notable peaks are observed in 2003, 2005, and 2007, with the highest spike in 2015, reaching $6,552.9360 million. This pattern suggests that specific years experienced a concentration of larger penalties, potentially due to heightened regulatory enforcement or exceptional cases of corporate violations. The years between these peaks show more moderate levels of penalties, indicating that extreme values heavily influence the average amounts. Additionally, the decline in penalty amounts after 2015 similar to violation frequencies, possibly reflecting improved compliance practices, shifts in regulatory enforcement, or fewer severe violations being reported.

**Figure 2: Total Penalty Amount between 2000 and 2022 (not standardized)**




*Note. – Data collected from the Violation Tracker in 2024. In thousand USD ($0,000).*

**Environmental Violations by Type**

Zooming into the offense groups of environmental regulations several observations can be made. Overall, the data contains 20 distinct environmental violations (Table 4) of which 5,494 observations could not be linked to a specific environmental violation (57.35%). More specifically, the largest group of environmental regulations are 2,267 air pollution violations, accounting for 23,67% of all violations. Followed by the second largest group hazardous waste violations with 463 observations (4.83%), and the third group water pollution violations, accounting for 404 observations (4.22%).

**Table 4: Summary Statistics of Primary Environmental Offenses (2000 - 2022)**

| Primary Environmental Offenses | Freq. | Percent | Cum. |
|---|---|---|---|
| MTBE violation | 23 | 0.24 | 0.24 |
| PCB violation | 6 | 0.06 | 0.30 |
| PFAS violation | 16 | 0.17 | 0.47 |
| Air pollution violation | 2,267 | 23.67 | 24.14 |
| Asbestos violation | 6 | 0.06 | 24.20 |

| | | | |
|---|---|---|---|
| Drinking water violation | 5 | 0.05 | 24.25 |
| Energy conservation violation | 12 | 0.13 | 24.38 |
| Environmental violation | 5,494 | 57.35 | 81.73 |
| Fuel economy (CAFE) violation | 1 | 0.01 | 81.74 |
| Hazardous waste violation | 463 | 4.83 | 86.57 |
| Lead violation | 22 | 0.23 | 86.80 |
| Mining environmental violation | 40 | 0.42 | 87.22 |
| Oil or gas drilling violation | 217 | 2.27 | 89.49 |
| Oil spill | 25 | 0.26 | 89.75 |
| Pesticide violation | 105 | 1.10 | 90.84 |
| Pipeline safety violation | 275 | 2.87 | 93.72 |
| Radioactive waste violation | 3 | 0.03 | 93.75 |
| Solid waste violation | 161 | 1.68 | 95.43 |
| Underground storage tank violation | 34 | 0.35 | 95.78 |
| Water pollution violation | 404 | 4.22 | 100.00 |
| **Total** | **9,579** | **100.00** | |

*Note. – Data collected from the Violation Tracker in 2024.*

**Industries**

For the industry analysis, the NAICS (North American Industry Classification System) classification is used to categorize the data into 18 different industries. NAICS is a standardized system used to classify companies into industries based on their economic activities, with the first two digits of the NAICS code representing broader industry groups. Of the 21 broader NAICS industries, our dataset includes only 18. The industries “Management of Companies and Enterprises,” “Educational Services,” and “Public Administration” are not included in our sample. The more detailed merging process is described in detail in chapter 5.2.1. As shown in the table below (Table 5), nearly half of the 9,579 violations are in the manufacturing industry, making it the most represented sector in the dataset. This could be attributed to the industry's complex and resource-intensive operations, which often involve extensive supply chains and significant environmental impacts, increasing the likelihood of regulatory breaches. In contrast, the "Other services" sector accounted for only 14 violations, which is the sector with the fewest penalties.

**Table 5: Frequency of Environmental Offenses across Industries (2000 – 2022)**

| Industry | Freq. | Percent | Cum. |
|---|---|---|---|
| Accommodation and Food Services | 36 | 0.38 | 0.38 |
| Administrative and Support and Waste Management and Remediation Services | 529 | 5.52 | 5.90 |
| Agriculture, Forestry, Fishing and Hunting | 21 | 0.22 | 6.12 |
| Arts, Entertainment, and Recreation | 17 | 0.18 | 6.30 |
| Construction | 152 | 1.59 | 7.88 |
| Finance and Insurance | 88 | 0.92 | 8.80 |
| Health Care and Social Assistance | 82 | 0.86 | 9.66 |
| Information | 100 | 1.04 | 10.70 |
| Manufacturing | 4,577 | 47.78 | 58.48 |
| Mining, Quarrying, and Oil and Gas Extraction | 1,456 | 15.20 | 73.68 |
| Non-Classifiable Establishments | 243 | 2.54 | 76.22 |
| Other Services (except Public Administration) | 14 | 0.15 | 76.36 |
| Professional, Scientific, and Technical Services | 16 | 0.17 | 76.53 |
| Real Estate and Rental and Leasing | 57 | 0.60 | 77.13 |
| Retail Trade | 460 | 4.80 | 81.93 |
| Transportation and Warehousing | 794 | 8.29 | 90.22 |
| Utilities | 716 | 7.47 | 97.69 |
| Wholesale Trade | 221 | 2.31 | 100.00 |
| **Total** | **9,579** | **100.00** | |

*Note. – Data collected from the Violation Tracker in 2024.*

**Company Characteristics**

To get an understanding of the companies that are represented in the dataset by size, the asset value will be considered as size reference. Using the final long-term dataset it can be seen that the data contains 9,541 observations. Examining companies by their size the smallest asset value after winsorization is around $124 million. The maximum asset size however can be found to be $552,000 million, and therefore it can be concluded that the spread between company sizes is rather large. The mean company size in terms of asset value is estimated to be

$52,800 million while the median is much smaller with $1,270 million, implying that the data is skewed to the right due to a few very large companies in the sample, which consequently increase the mean strongly (see Appendix G).

Additionally, to be able to get an overview of companies general ESG performance, the total ESG grade was examined (see Appendix H). However, from the companies contained in the ESG dataset only 261 distinct companies could be merged to the previously merged data, which is why information on ESG data is limited. Of the 261 distinct companies, 53 companies have the highest ESG rating "A" (20.31%), 36 companies have the rating "B" (13.79%), 19 companies have the rating "BB" (7.28%), and finally 153 companies have the lowest rating "BBB" (58.62%).

### 4.2 Fixed-Effect Panel Regression Results & Analysis

The fixed-effect panel regression analysis examines the relationship between penalty amounts paid by firms due to CELs and the firms' financial performance, accounting for year-fixed effects and unobserved firm-specific characteristics. The coefficients for the year dummy variables indicate that the revenue of companies consistently increased over time relative to the base year 2000, showing a statistically significant upward trend (see Appendix I). For instance, the coefficients for 2010 (0.5607, $p < 0.000$) and 2020 (0.8207, $p < 0.000$) reflect a substantial and steadily increasing revenue throughout the observation period, suggesting that there are external macroeconomic factors driving overall revenue growth across companies. More interestingly, looking at the key variable for interpretation, the coefficient for penalty amounts is -0.021 ($p < 0.000$). Therefore, it can be concluded that there is a negative and statistically significant relationship between penalties and the revenue of companies. Specifically, since the regression model is a log-log regression, a 1% increase in the penalty amount, holding everything else constant, is associated with an approximately 0.02% decrease in revenue, controlling for year-fixed effects. Furthermore, the R squared value of 0.3413 (within groups) suggests that the model explains approximately 34% of the variation in revenue within firms over time. To improve the R squared of the regression analysis, the model was run again including multiple additional control variables such as the EBIT, and multiple financial ratios (Table 6). This extended model enhances the explanatory power, as indicated by an increased R squared within-firm value of 0.4281 (43%).

**Table 6: Output of Fixed Effect Panel Regression Analysis**

**of Penalty Amount on Revenue**

| **log_revt_w** | **Coefficient** | **Robust std. err.** | **t** | **P>\|t\|** | **[95% conf.** | **interval]** |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | -.0147251 | .0039161 | -3.76 | 0.000 | -.0224139 | -.0070364 |

*Note. – Model including Control Variables (see Appendix I for full Model).*

These findings reinforce the robustness of the observed negative relationship between penalties and revenue (coefficient = -0.0147; $p = 0.000$) while incorporating a broader set of financial performance controls. So far, the regression analysis has been performed on the total yearly revenue of companies as the dependent variables. However, since a penalty amount that must be paid due to a regulatory violation is a cost item on the income statement it only indirectly influences the top-line (thus the revenue) of companies through a decrease in sales and consequently damage to reputation for instance. Consequently, it is additionally interesting to use the EBIT of companies as a dependent variable, since this financial metric includes all costs that have incurred to the company. The coefficient for the penalty amount with EBIT as the dependent variable is 0.0420 ($p = 0.137$), indicating a positive however insignificant relationship between the two variables (see Appendix I). While these results cannot be interpreted due to insignificance, the tendency shows a conflicting trend compared to the revenue, indicating that penalties might not have any impact on financial profitability.

Considering the results described above, the hypothesis of this study that paying a penalty has no significant long-term effect on firms' financial performance can be rejected, especially when using the revenue as financial metric. The negative relationship between penalty amounts and the revenue suggests that penalties might have a deterring influence on the overall financial performance of a company. One possible explanation is that penalties might damage a company's reputation, eroding customer trust and reducing the overall demand for the firm's product or services. Hence, reputational harm could lead to lost sales opportunities and thus paying a penalty can have an indirect impact on top-line financial performance. Moreover, penalties may divert management's focus toward resolving compliance issues and improving regulatory conformity, which may limit their ability and resources to pursue growth-oriented initiatives. Disruptions caused by penalties, such as increased oversight or regulatory scrutiny, may hinder the agility in responding to market opportunities. In contrast, the positive relationship tendency between penalty amounts and EBIT could reflect a company's ability to mitigate the direct financial impact through operational adjustments, such as cost-cutting measures or efficiency improvements. Larger companies in particular may absorb penalties without significant disruption to profitability due to their scale and flexibility (see chapter 5.3). The findings of the long-term analysis underscore the complexity of CELs and monetary penalties as a regulatory tool. The statistically significant influence on company's top-line financial performance (revenue) opposed to the positive, and negligible impact on profitability suggest that the indirect effect through reputational damage is much more relevant than the actual monetary amount. Nevertheless, even though indirectly, it can be stated that there is a negative impact of CELs on companies' long-term financial performance.

### 4.3 Event Study Result & Analysis

The event study examines the short-term effect of CELs on the stock returns of companies. In particular, the behavior of stock returns in the period following the announcement of the penalty imposed on the company is analyzed. The key variable "penalty", which represents the monetary amount of a penalty, has a coefficient of 0.000009 and a p-value of 0.895 (Tabel 7).

**Table 7: Output of Event Study Regression Analysis of Penalty Amount on Average Abnormal Return**

| **mean_aret_w** | **Coefficient** | **std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | 8.79e-06 | .0000669 | 0.13 | 0.895 | -.0001224 | .00014 |

Note. - *Model including Control Variables (see Appendix J for full Model).*

Since this is a level-log regression this would mean that a 1% increase in the penalty amount, keeping all other variables constant, is associated with a 0.000009 percentage point increase in the average abnormal return. This implies a very minimal positive relationship, meaning that larger penalties may be associated with higher abnormal returns. However, due to the high p-value, this relationship is not statistically significant and should be interpreted with caution.

The summary of the regression shows a weak fit of the overall model. The F-statistic is 0.48 with a corresponding p-value of 0.8681, indicating that the independent variables taken together do not significantly explain the variation in the dependent variable. The R square value is extremely low at 0.0009, which means that the model explains only 0.09% of the variance of the mean abnormal returns. The Root Mean Squared Error is 0.0105 and reflects the average deviation of the predicted values from the observed values. The results indicate that the selected variables have minimal explanatory power, suggesting that short-term stock price reactions may be influenced by unstudied factors. Using the cumulative return as the dependent variable leads to almost the same results as with the average abnormal return (Appendix J). Therefore, only the average abnormal return is used for further analysis.

Overall, the results of this event study suggest that the short-term impact of CEL, as measured by penalty amounts, on stock returns is limited. While the regression analysis shows a very small positive relationship between penalty amounts and abnormal returns, the lack of statistical significance suggests that this relationship is not robust. This weak effect combined with the minimal explanatory power of the model suggests that factors other than penalty amounts and the additional control variables used may play a more important role in influencing short-term stock price movements. The lack of statistical significance for the financial variables highlights the limited scope of the current model in capturing the main drivers of stock price behavior. It is possible that investors consider other factors such as the overall financial condition of the company, market conditions, or even the perceived long-term reputational impact of environmental violations in their reactions to such events. Furthermore, the model's low explanatory power underscores that short-term stock price reactions can be influenced by unmeasured variables such as investor sentiment or firm specific characteristics, highlighting the complexity of market behavior.

# 5 Deep Dives

This chapter presents three in-depth analyses that examine how the financial impact of environmental liabilities varies depending on the type of regulation violated, the industry, or company size. Each section includes descriptive statistics, a panel regression for long-term effects and an event study for short-term impacts. For the descriptive statistics it was chosen to exclusively examine the long-term dataset, since otherwise the results will mainly be redundant. The first deep dive examines violations with the most counts (count over 200) in the study period. The second explores differences across the three industries with the most overall violations, while the third evaluates how firm characteristics, like company size influence financial outcomes. Together, these analyses provide a deeper understanding of the impact of envioronmental liabilities on financial performance of companies in the U.S.

## 5.1 Industry Deep Dive

This section examines the impact of CEL on the financial performance of companies in different industries. A fixed-effect panel regression is used to assess the long-term effects, while an event study is used to capture the short-term effects. To ensure a solid analysis, the three industries with the most entries in the dataset were first selected and examined.

### 5.1.1 Data Preparation

While the VT dataset provides an industry classification across 49 detailed industries, the NAICS classification groups these into 21 higher-level industries. For this analysis, we use the NAICS classification to assign violations to industries because it provides a broader and more consistent categorization. Additionally, because this section focuses on the three industries with the most entries, the broader NAICS industry classification increases the representativeness and comparability of the industries we select. Based on the first two digits of the NAICS codes, an industry classification was created using classification information provided by the U.S. Census

Bureau (U.S. Census Bureau 2024). Since two different data sets are used for the long-term and short-term analysis, separate preparation steps are required for both. The long-term industry dataset is created by merging the obtained industry classification file to the long-term_adjusted file. Prior to the merge the long-term_adjusted file needs to be prepared by extracting the first two digits of the NAICS number, which serves as key variable in the merge. Subsequentely an m:1 merge is performed leading to a dataset containing a new variable “industry_group”, which assigns each of the violations to one of the 21 industries. Only observations that are present in both dataset are retained, resulting in the removal of three observations are deleted as these correspond to NAICS industries that are not represented in this study’s dataset. For the long-term dataset, the penalty amount needs to be aggregated by summarizing it for each individual company-year combination. In addition the non-standardized penalty amount is created at the company year level to be used later in descriptive statistics. Afterwards, all duplicate entries for each unique company year combination were removed. Both penalty variables are winsorized and the standardized penalty amount is transformed by using the log which is required for further robust analyses. For the short-term dataset, the shortterm_data_adjusted dataset is used, in which the penalty amounts already are collapsed by company and penalty date. The first thing is to merge this dataset with the industry classification file using the first two digit of the NAICS number as the key variable. Then the penalty amount variable is winsorized and logarithmically transformed to ensure robustness.

### 5.1.2 Descriptive Statistics

This analysis focuses on the three industries with the most violations in the dataset. The first industry, “Manufacturing”, accounts for a majority of the dataset with 47.78% of the total observations. The second industry, “Mining, Quarrying and Oil and Gas Extraction” (hereafter referred to as mining), accounts for 15.2% of the dataset. Finally, the “Transportation and

Warehousing” industry (hereinafter referred to as transportation) accounts for 8.29% of the observations (see Table 5).

Together, these industries form a diverse yet focused basis for examining the impact of environmental liabilities of companies in different sectors. An analysis of the penalty amounts across the three industries shows that the minimum and maximum values are identical, with a minimum of $5,000 and a maximum of $117.1538 million (see Appendix Q). This is due to the winsorization process, which replaces values below the 1st percentile and above the 99th percentile to limit the influence of extreme outliers. As all three sectors are subject to high penalties, their highest penalties are replaced in this process. To provide a clearer picture, a table is created showing the original highest and lowest fines before winsorization. This shows the differences between the three sectors in terms of the penalty amounts. In the manufacturing sector, fines range from a minimum of $5,000 to a maximum of $810.2 million (Table 9), revealing significant differences within the industry. In the mining sector, fines range from $5,000 to $5.15 billion (Table 9), which is the largest range among the industries analyzed. In contrast, the range in the transportation industry is narrower, with fines starting at $408 and reaching a maximum of $220 million (Table 9). These figures illustrate that the mining industry has by far the highest fines, which is consistent with the expectation that pollution in this sector is likely to be particularly severe.

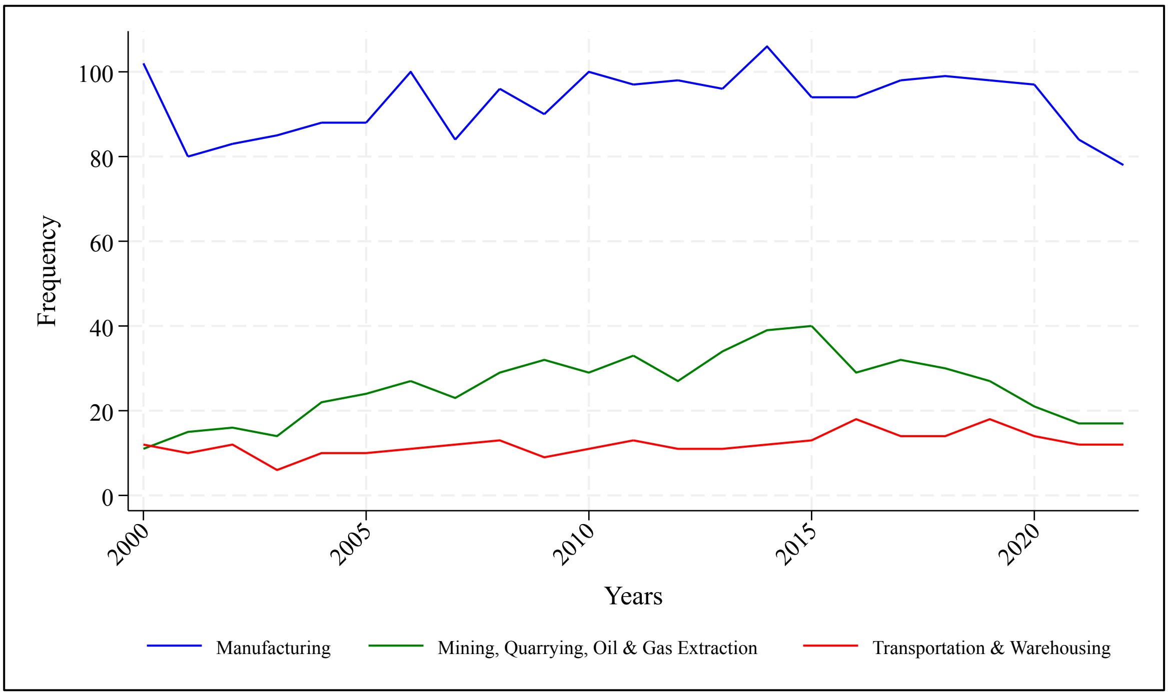
**Table 8: Penalty Amount across Industries (2000 – 2022)**

| **Industries** | **N** | **Min** | **Max** |
|---|---|---|---|
| Manufacturing | 2,135 | 5 | 810,222.1 |
| Mining, Quarrying, and Oil and Gas Extraction | 558 | 5 | 5,150,293 |
| Transportation and Warehousing | 278 | 5 | 220,105 |

*Note. – Data collected from the Violation Tracker in 2024. In thousand USD ($0,000).*

In the next step, the frequency of violations over time is examined across the three industries. As seen in Figure 5, the manufacturing industry consistently exhibits the highest frequency of violations, with relative stability over the years but a slight decline recently. The mining industry shows an upward trend in violations until 2015, followed by a notable decline, suggesting changes in industry practices or regulations. The transportation sector consistently has the lowest violation frequency, with only minor fluctuations over time. Overall, the graph highlights the dominance of manufacturing in violation frequency and the differing trends across industries.

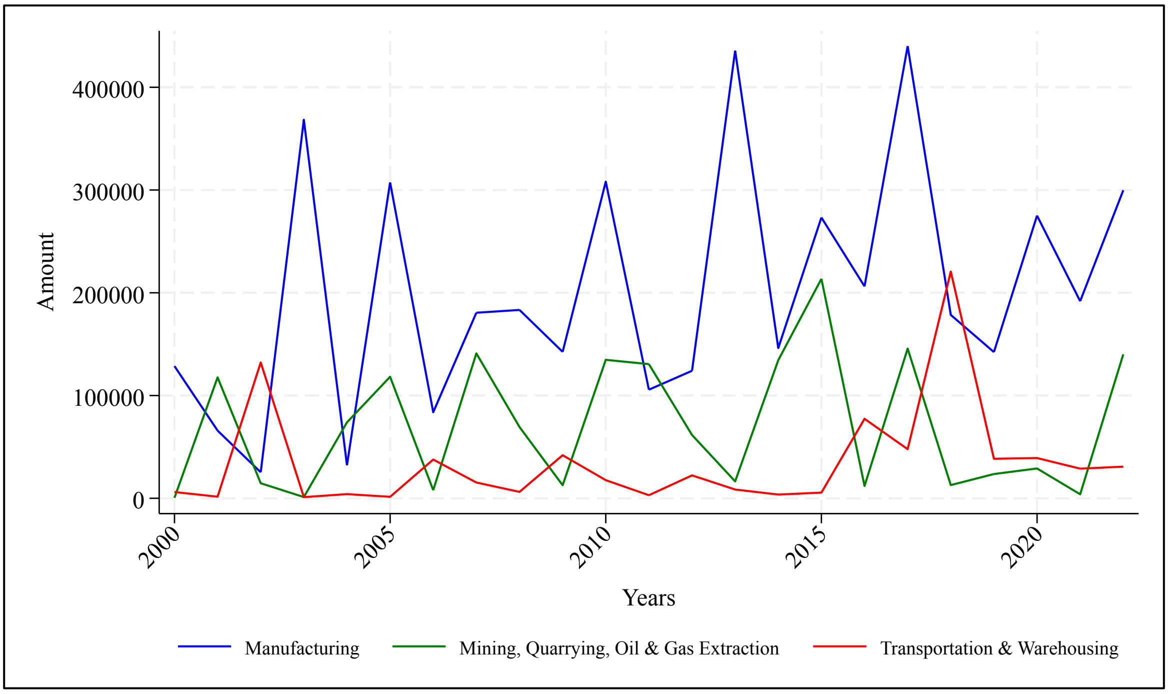
**Figure 3: Violation Frequency across Industries (2000 – 2022)**




*Note. – Daa collected from the Violation Tracker in 2024,*

After examining the frequency, the annual penalty amounts in the various sectors are analyzed. For this analysis, the non-standardized penalty amount is used as it provides clearer insights into the penalty amount variable than the one standardized by asset value. While standardizing is useful in many contexts, it could obscure the absolute level of penalties, which is crucial for understanding their financial impact and differences at the industry level. Figure 6 shows that the manufacturing industry exhibits the greatest fluctuations in fine amounts, with several clear peaks indicating years with exceptionally high fines. The mining sector also shows fluctuations, albeit with fewer and less pronounced peaks than in the manufacturing sector. The transportation sector, on the other hand, remains relatively stable and has the lowest fines over the entire period.

**Figure 4: Penalty Amount across Industries (2000 – 2022)**




*Note. – Data collected from the Violation Tracker in 2024. In thousand USD ($0,000).*

### 5.1.3 Panel Regression across Industries

In the following, a panel regression with fixed effects, which has already been carried out for the entire sample, is now carried out for the three selected sectors "Manufacturing", "Mining" and "Transportation". The log-log regression is performed with two different dependent variables, revenue and EBIT. First, the results are presented for each industry. Afterwards they are compared with each other and finally the differences are analyzed.

**Manufacturing**

The regression results for the manufacturing industry show a statistically significant negative relationship between penalty amounts and revenue. The coefficient for penalty amounts is

-0.0389 with a p-value of 0.000, indicating that holding all other variables constant, a 1% increase in the penalty amount results in a 0.0389% decrease in revenue (see Appendix R). As for the fit of the model, the within R-squared of 0.0878 suggests that about 8.78% of the variation in revenue within firms over time is explained by the model. In addition, the overall R-squared of 10.56% indicates that the total variation in revenue is explained by the independent variables. These low R-squared values suggest that other unobserved factors may play an important role in influencing revenue. In contrast, the regression with EBIT as the dependent variable shows a coefficient of 0.0757, which indicates a positive relationship between EBIT and penalty amounts (see Appendix R). However, the high p-value of 12.5% indicates that the relationship is not statistically significant, suggesting that penalty amounts do not have a significant impact on EBIT. The model fit for the EBIT regression is significantly weaker with a within R-squared of 5.85 % and an overall R-squared of 3.31 %. As with revenue, these low R-squared values seem to indicate that other unobserved factors may play an important role in influencing EBIT.

**Mining, Quarrying, and Oil and Gas Extraction**

Both regression analyses for the mining industry show a positive but statistically insignificant relationship between the penalty amounts and revenue & EBIT. In the revenue regression, the penalty amount variable has a coefficient of 0.003 ($p = 0.818$), which would mean that a 1% increase in the penalty amount is associated with an estimated 0.003% increase in revenue, ceteris paribus (see Appendix S). The EBIT regression results yield a coefficient of 0.072 ($p = 0.637$), indicating a positive relationship (see Appendix S). However, the lack of statistical significance in both regressions indicates that the penalties do not significantly affect financial performance in this industry. The R-squared values of 15.59% for the revenue model and 11.97% for the EBIT model show that a significant portion of the fluctuations in financial performance are likely due to unobserved factors that are not captured in the regression.

**Transportation and Warehousing**

The regression results for the transportation industry show contrary relationships between penalty amounts and financial performance. In the revenue regression, the coefficient for the amount of penalties is -0.0064 (see Appendix T), indicating a negative relationship between penalties and revenue. Conversely, the regression of EBIT shows a positive relationship with a coefficient of 0.0445 (see Appendix T). However, both coefficients are highly statistically insignificant ($p = 0.596$ and $p = 0.335$), making it impossible to draw definitive or reasoned conclusions about the impact of penalties on financial performance. Furthermore, the low R-squared values indicate that revenue and EBIT are likely to be influenced by unobserved factors that are not captured in the model.

**Interpretation and Comparison across industries**

Among the three economic industries, the only statistically significant relationship between penalty amounts and financial performance can be observed in the regression of revenue for the manufacturing industry. The result shows a negative relationship where higher penalty amounts are associated with a decrease in revenue. This indicates that penalties represent a measurable financial burden for manufacturing companies, likely reflecting the industry's vulnerability to penalties. In contrast, no statistically significant correlation was found between the amount of penalties and revenue or EBIT in the mining and transportation sectors. This suggests that penalties do not appear to have a direct financial impact on these sectors, possibly reflecting greater resilience or the ability to absorb penalties through operational or financial buffers. Notably, EBIT shows a more consistent relationship with penalties across all sectors, with positive coefficients in each regression, although not reaching statistical significance. This pattern suggests that penalties do not directly affect profitability, as companies could adjust costs or other operational factors to mitigate the financial impact. Revenue, on the other hand, shows a mixture of positive and negative relationships with penalties, with statistical significance only observed in the manufacturing industry. These variations suggest that the impact of penalties on revenue is more dependent on industry-specific factors, such as reputational damage or sensitivity of customer demand, which vary from industry to industry. Looking additionally at the model fit it can be seen that while mining has the highest R-squared values (15.59% for revenue and 11.97% for EBIT), overall, these values are relatively low for all industries. This suggests that financial performance in all three industries is likely to be influenced by a number of unobserved factors, such as market conditions, management practices or industry-specific dynamics, that are not captured by the models. These results highlight the complexity of assessing the financial impact of penalties, as industry-specific dynamics and external factors can play an important role. The significant negative relationship in the manufacturing industry reflects vulnerability to penalties, which is likely due to stricter regulations, public scrutiny and the company's customer intimacy. In contrast, the lack of significant results in the mining industry suggests that financial buffers, such as long-term contracts or capital reserves, mitigate the impact of fines. The transportation industry shows mixed results, with penalties likely being treated as a routine cost that is offset by operational efficiencies or industry norms.

### 5.1.4 Event Study across Industries

In order to analyze the short-term impact of penalties on financial performance, the event study regression previously conducted in the general analysis is now applied to the three selected industries. The dependent variable in this analysis is the average abnormal return, which is regressed on the logarithm of the penalty amount together with additional financial control variables. Consequently, a level log regression model is used for this short-term analysis.

**Manufacturing industry**

The regression results show a positive coefficient for the penalty amount of 0.00003, indicating a positive relationship between penalty amounts and average abnormal returns (see Appendix

U). Specifically, holding all other variables constant, a 1% increase in the penalty amount would lead to a 0.00003 percentage points increase in the average abnormal return. However, the result is statistically highly insignificant, as reflected in a p-value of 0.77, making it impossible to draw solid conclusions. Furthermore, the explanatory power of the model is extremely low, with an R squared value of 0.17%, which means that all independent variables together explain only 0.17% of the variation in average abnormal returns. Finally, the overall F-statistic (0.52 with a p-value of 0.8444) confirms that the model as a whole is not statistically significant.

**Mining, Quarrying, and Oil and Gas Extraction**

For the mining industry, the coefficient of penalty amounts is 0.0002, indicating a positive relationship between penalty amounts and average abnormal returns (see Appendix U). However, the p-value of 0.381 shows that the coefficient is not statistically significant, thus no meaningful conclusions can be drawn. The explanatory power of the model is also extremely low with an R squared value of 0.41%, meaning that the independent variables together explain only 0.41% of the variation in average abnormal returns. In addition, the overall F-statistic (0.43 with a p-value of 0.9015) confirms that the model as a whole is not statistically significant.

**Transportation and Warehousing**

For the transportation industry, the coefficient for the penalty amount is 0.0002, which indicates a positive correlation with the average abnormal return (see Appendix U). However, this correlation is not statistically significant (p-value: 0.513). The overall R squared value is higher compared to the other industries with a value of 5.68 %, which indicates a modest improvement in the explanatory power of the model. It is worth noting that the F-statistic is statistically significant (p-value $<$ 0.001), indicating that the model is statistically significant, which is likely due to the influence of other control variables rather than the penalty amount itself.

**Table 9: Aggregated Overview on Regression Results across Industry**

| | Fixed-effect panel regression (long-term) | | | | Event Study regression (short-term) | |
|---|---|---|---|---|---|---|
| Dependent variable | Revenue | | EBIT | | Mean abnormal return | |
| | Coefficient Penalty Amount | p-value | Coefficient Penalty Amount | p-value | Coefficient Penalty Amount | p-value |
| Manufacturing | -0.0389 | 0.000 | 0.0757 | 0.125 | 0.00003 | 0.770 |
| Mining | 0.0034 | 0.818 | 0.0718 | 0.637 | 0.0002 | 0.381 |
| Transportation | -0.0064 | 0.596 | 0.0445 | 0.335 | 0.0002 | 0.513 |

*Note. – All Models including Control Variables (see Appendix for full Models).*

**Interpretation and Comparison across Industries**

Across all three industries, the coefficients for the amount of penalties show a positive relationship with average abnormal returns, suggesting a potential increase in stock prices as penalties increase. However, none of these coefficients are statistically significant, suggesting that this trend cannot be proven with certainty. This lack of significance means that the amount of penalties may not have a measurable impact on short-term stock price performance. While the penalties could have an impact on other areas such as the company's reputation or operations, this impact is not directly reflected in investor reactions or market performance. The low R squared values across all industries indicate that the variables included in the model explain only a very small proportion of the variation in average abnormal returns. This suggests that other unobserved factors such as broader market conditions (e.g. economic news or interest rate changes) or investor sentiment (e.g. perception of the company's reputation, past violations or future profitability) are likely to influence stock performance after penalties. In the transportation sector, the overall model is statistically significant. However, this is probably due to other independent variables rather than the amount of the penalties. In contrast, the regression model is insignificant for both manufacturing and mining. In manufacturing, this could reflect the long-term nature of reputation effects that are not captured in a short-term event window. For the mining sector, the lack of significance could indicate that penalties are perceived as a routine cost of doing business in a highly regulated industry. Shareholders may already factor such penalties into their valuation, resulting in minimal short-term market reactions. In addition, the stability provided by long-term contracts or capital reserves can boost investor confidence,

## 6 Conclusion & Outlook

This study examines the impact of CEL's on the financial performance of companies in the U.S. and provides a comprehensive analysis by distinguishing between short-term and long-term impacts. Through such a dual perspective the study provides insights into the relationship between CEL and their financial performance. The objective of this analysis is to assess whether current measures and penalties for companies that violate environmental regulations are effective. The analyses reveal a clear pattern: Although a statistically significant long-term impact on financial performance can be identified in some cases, the short-term impact remains inconclusive, emphasizing the need to focus on long-term outcomes to fully understand the financial implications of environmental liabilities.

The long-term regression results show a statistically significant negative relationship between the revenue and penalties, while the relationship between penalties and EBIT is positive but not statistically significant. These results suggest that penalties indirectly affect a company's top-line performance, likely due to reputational damage or reduced customer confidence. Conversely, although penalties are directly recorded as "Other Expenses" in the income statement, no significant impact on profitability measured as EBIT is observed. This could be explained because larger companies are able to mitigate the financial impact through cost-cutting measures or operational adjustments. In contrast, the short-term analysis yields no statistically significant results. Although the relationship between penalties and average abnormal return is slightly positive, the high p-value, non-significant F-statistic, and the overall poor fit of the model indicate that short-term stock price movements are influenced by unmeasured factors, such as investor sentiment or broader market conditions. The results show a clear difference between the short- and long-term impact of environmental penalties. While the short-term impact on financial metrics is minimal, the statistically significant long-term impact on revenue highlights the importance of reputational damage and strategic responses when assessing the financial impact of environmental violations.

Following the analysis of the entire sample, the deep dives examine the financial impact of penalties from different perspectives with a focus on different types of violations, industries and company sizes. Among the violation types, air pollution and hazardous waste violations result in statistically significant revenue losses, likely due to reputational damage and increased regulatory scrutiny as these violations are well known and attract public and media attention. Conversely, pipeline safety violations lead to a significant reduction in profitability (EBIT) probably due to direct costs such as business interruption, legal costs and safety investments. The industry analysis only shows a statistically significant negative relationship between revenue and penalties in the manufacturing industry, highlighting its vulnerability to penalties due to stricter regulations, whereas the mining and transportation industries are proving resilient. Across all sectors, EBIT remains statistically insignificant, suggesting that companies are effectively mitigating the direct costs of penalties to protect their profitability. Across company size, we find that smaller companies are more affected by penalties because they account for a larger share of their operating costs, while larger companies are better able to absorb penalties since they often treat them as routine costs. The short-term impact on stock performance is minimal and not statistically significant, suggesting that penalties are usually anticipated by investors or perceived as financially insignificant in the short term.

To conclude the obtained results make it necessary to reject the first null hypothesis, which states that penalties have no long-term effects on financial performance. Contrary to what was assumed, the results even show a statistically significant negative relationship between the penalty amount and long-term financial performance as measured by revenue. This is supported by both the general analysis as well as all three conducted deep dives. Furthermore, the second null hypothesis, which states that there is a negative effect from penalty amounts on the stock price return also has to be rejected. The study finds no statistically significant evidence for this hypothesis, both in the general analysis and in the three deep dives. This suggests that penalties have minimal immediate impact on stock prices, possibly due to investor expectations or the perception that penalties are financially insignificant in the short term.

The indirect long-term impact of corporate environmental liabilities on the revenue of companies, though small, has critical implications for businesses, investors, policymakers, and the larger society. The findings suggest that environmental regulatory violations, while not catastrophic for corporate financial health, do influence corporations and thus their competitive advantage over time. Concludingly, for corporations this signals the importance of a proactive management and a consistent monitoring of their environmental practices. Companies that deprioritize this, may over time face cumulative financial burdens through regular penalty payments and the implied consequences. Similarly, investors should consider corporate environmental liabilities as a risk factor when evaluating long-term investment opportunities. It can be stressed that incorporating ESG criteria into investment decisions is essential to identify enterprises capable of managing corporate environmental liabilities correctly. On the other hand, the results also bear significant implications to regulators and policymakers. The small impact of corporate environmental liabilities on the revenue of companies indicates a need for more robust regulatory frameworks that can help to align corporate behaviour with societal expectations. For instance, governments could increase the extent of corporate environmental liabilities by implementing more strict measures or increase penalty amounts. Stricter policies might have a more severe impact on the financial performance of companies and thus incentivize them to further improve their environmental compliance in the future.

Overall, due to conflicting results and low statistical credibility, the results of this study reveal several opportunities for further research. Since especially the short-term analysis did not result in an interpretable outcome, it could be conducted using different extents of the event and the estimation windows. Since there is a possibility that information leaks prior to the official announcement of a penalty, allowing the shareholders to already price in the event, extending the event window could have a differential impact on the results. Another improvement to the short-term effect analysis could be adding additional control variables such as external variables (e.g. interest rates) or industry-specific variables (e.g. production cycles) which also have an effect on the company's stock market performance at the time of the event. Adding more control variables could especially be interesting in the deep dives within this study, since particularly in those analyses the results appeared to be highly insignificant. While some results of the long-term analysis where in fact significant, adding more control variables including measurements for macroeconomic factors and public perception, could also improve the credibility of these results. Expanding the study to a larger sample size would also provide more robust insights into the relationship between penalties and financial performance. Moreover, comparing results across different regions could highlight variations in regulatory impacts and market reactions, offering a broader perspective. Furthermore, it could be interesting to examine more closely the other expenses on the income statements of companies that were penalized, in order to reveal whether companies absorb the costs of a fine by offsetting through cuts in other departments. Looking ahead, the evolving regulatory landscape and the growing importance of corporate environmental responsibility offer interesting opportunities for future research. As stakeholders place increasing importance on sustainability, reputational impacts and market responses to environmental penalties may change, making longitudinal studies particularly valuable. Furthermore, as data availability improves, future researchers could also examine penalties in emerging industries such as renewable energy or technology to determine whether the financial consequences differ from those of traditional industries. Another aspect for future research is the investigation of ESG ratings and their relationship to environmental breaches. In particular, examining the changes in a company's ESG rating before and after a breach could provide valuable insights into the direct impact of such violations on the perception of a company's sustainability. In addition, it could be investigated whether market reactions to environmental penalties vary depending on a company's pre-existing ESG score. This would help determine whether companies with higher ESG ratings experience stronger or weaker investor reactions. By filling these gaps and extending the findings of the current study, future research can provide a more comprehensive understanding of how penalties affect financial performance in different contexts.

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Zulfikar, Rizka. 2018. ‘Estimation Model and Selection Method of Panel Data Regression: An Overview of Common Effect, Fixed Effect, and Random Effect Model’. *JEMA: Jurnal Ilmiah Bidang Akuntansi* 9 (2): 1–10.

## Appendix

### Appendix A: Diagnostic Testing of the Dataset

As there are two datasets, one will be collapsed for the entire penalty amount of each company per year (long-term data) and one collapsed per penalty date for each company (short-term data), it needs to be chosen which dataset is used for diagnostic testing. However, since the short-term dataset builds on top of the same variables as in the long-term data, it is sufficient to only use the long-term data for testing.

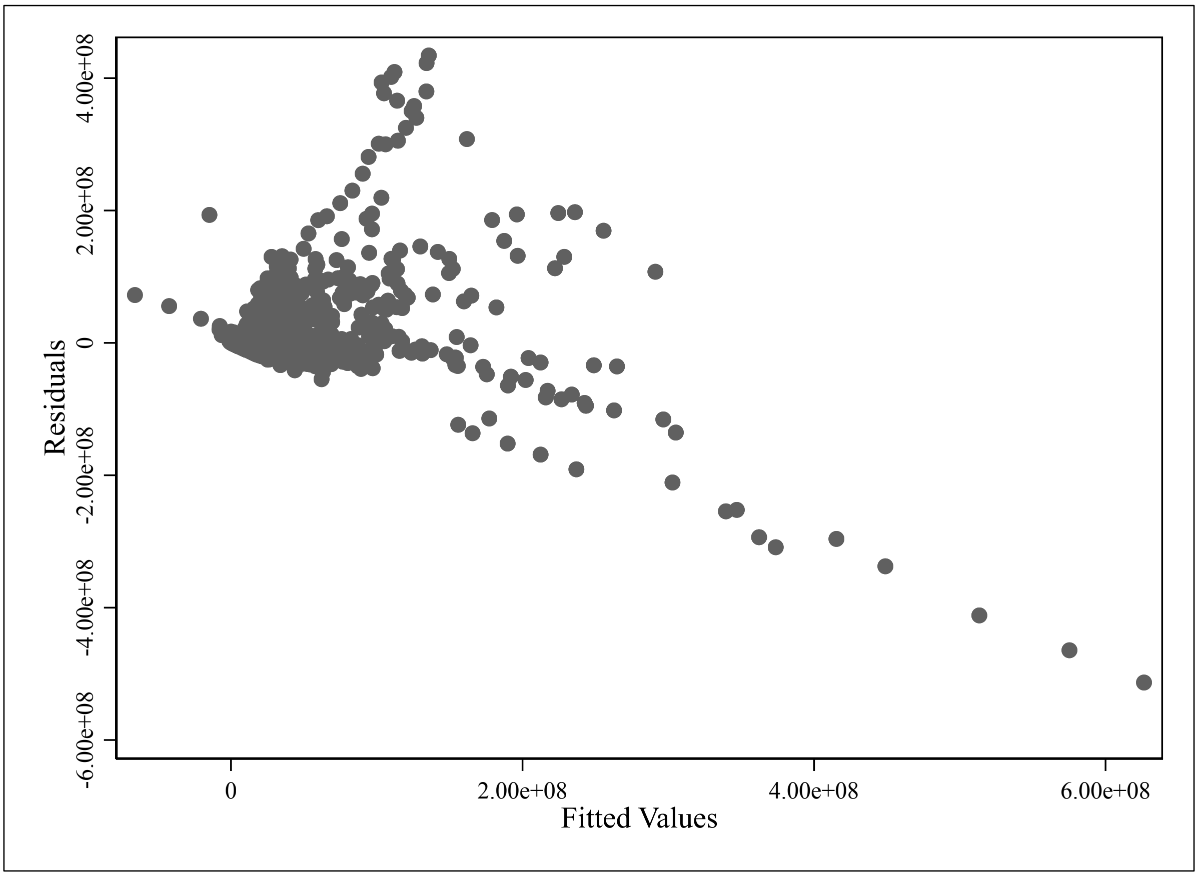
### Long-Term Data

To prepare the final long-term dataset for the regression, several preparational steps need to be taken. First, it is crucial to summarize the total penalty amount per parent company-year combination to have unique values for each combination. To do so, the total penalty per company and year is calculated by summing “penalty” within each parent company-year group and duplicates are removed. Moreover, the “tic” variable was encoded as “numeric_tic” to facilitate numeric panel data handling in the later analysis.

To initially determine which type of regression should be used for the long-term analysis, the Hausman test was applied to the dataset. This test is used to check whether a fixed-effect regression or a random-effect regression should be used to estimate the model. Since a highly significant p-value of 0.000 (see Appendix B) was obtained, the null hypothesis is rejected, which states that the random effect estimator is consistent and efficient. The consequence of such a finding is that in the following analysis a fixed effect regression should be used as it is more appropriate for the data structure (Sheytanova 2015).

Performing a test for homoscedasticity is essential to ensure the accuracy of the standard errors of the model. The presence of heteroscedasticity can lead to biased standard errors, potentially leading to incorrect conclusions regarding the statistical significance of variables and the magnitude of their effects (Vogelsang 2012). To visually assess the presence of heteroscedasticity, a plot of residuals against fitted values was generated. In this plot, the x-axis represents the fitted (predicted) values from the regression model, whereas the y-axis represents the residuals, which are the differences between observed values and fitted values. Patterns or clustering in the spread of residuals can indicate heteroscedasticity, where the variance of residuals changes with the fitted values. The plot provides a preliminary visual check before performing the formal modified Wald test for heteroscedasticity across panels (Figure 9).

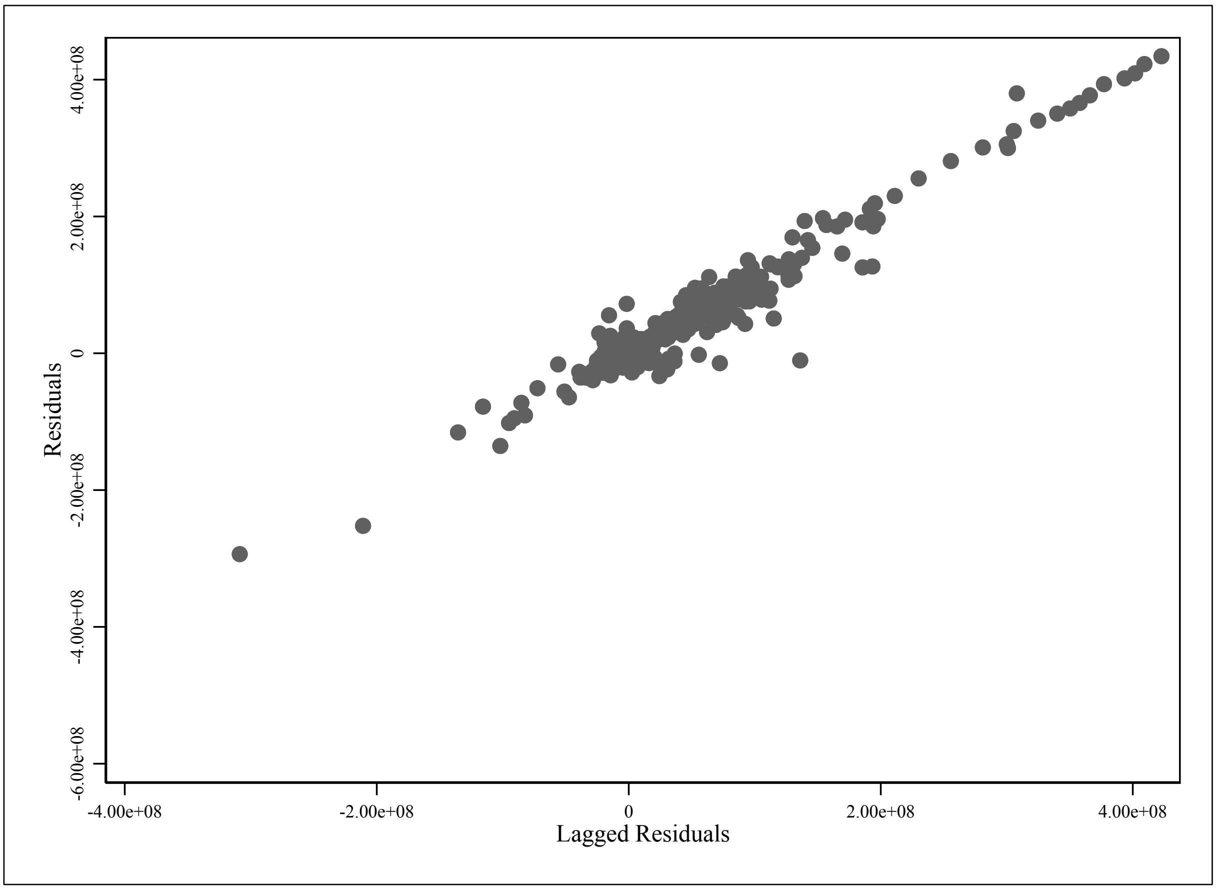
**Figure 9: Residuals vs. Fitted Values Plot for Heteroscedasticity Assessment**




Performing the modified Wald Test on the data results in a p-value of 0.000, which means that the null hypothesis that there is homoscedasticity across the panels is rejected (see Appendix C). To account for the existing heteroscedasticity, robust standard errors have to be used in the further regressions (Vogelsang 2012).

Since robust standard errors are used to account for autocorrelation, conducting an additional autocorrelation test is not strictly necessary. However, for the sake of thoroughness, lagged residuals were generated and regressed on the original residuals to formally test for autocorrelation (Figure 10). Plotting this, on the x-axis the residuals from the previous time period (lagged values of residuals) are plotted. The y-axis shows the residuals from the current time period. If a linear pattern is observed in the graph, the data could be positively autocorrelated over time, meaning that a positive residual in one period is likely to be followed by a positive residual in the next period.

**Figure 10: Residuals vs. Lagged Residuals Plot for Autocorrelation Assessment**




Given that the graph shows a strongly positive linear relation, and the p-value for the regression of residuals on lagged values is highly significant (0.000) (see Appendix D), the presence of positive autocorrelation can be confirmed. The application of robust standard errors is thus a beneficial adjustment to address this issue in the model.

Furthermore, testing for multicollinearity is important, as high correlations between independent variables can distort the estimated coefficients, making them unstable and unreliable and reducing the overall statistical power of the model. For this, the variance inflation factor (VIF) has been used. If a variable has a VIF value above ten, its necessity in the model should be considered (Table 13).

**Table 13: VIF-Test for Multicollinearity (long-term)**

| Variable | vif | 1/vif |
|---|---|---|
| Asset value | 1.95 | 0.5124 |
| EBIT | 1.92 | 0.5221 |
| Return on assets | 1.67 | 0.5983 |
| Gross profit margin | 1.56 | 0.6396 |
| Net profit margin | 1.52 | 0.6560 |
| Debt-to-asset ratio | 1.11 | 0.9045 |
| Return on equity | 1.07 | 0.9373 |
| Penalty amount | 1.00 | 0.9969 |
| Debt-to-equity ratio | 1.00 | 0.9978 |
| **Mean vif** | **1.42** | |

The table shows that all values are below two, proving that there is no multicollinearity between the independent variables (Daoud 2017).

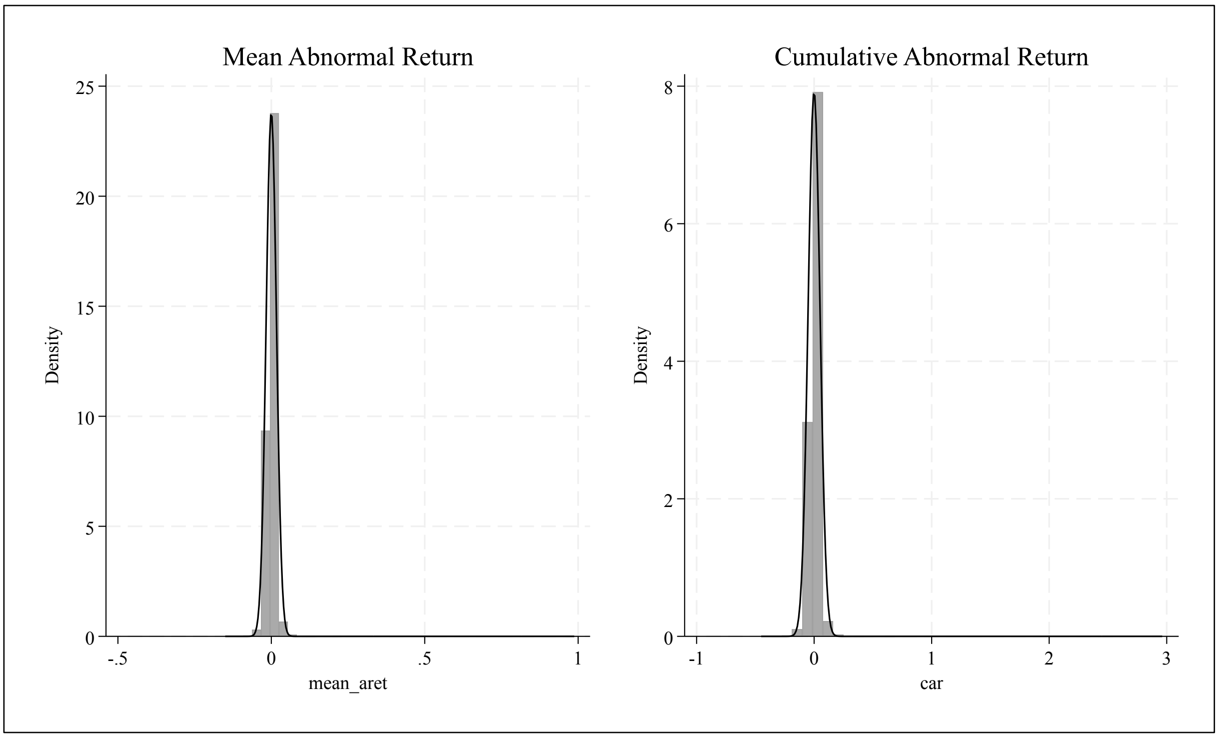
Next the winsorization method has been performed on all relevant variables to adjust for outliers. Extreme values over the $99^{th}$ percentile or below the $1^{st}$ percentile are replaced with the respective boundary value. For the long-term data this method is applied to the variables "roa", "roe", "npm", "gpm", "debt_at", "de_ratio", "revt", "ebit" and "at". As the variable for penalty amount needs to be collapsed in a later phase of the analysis, the winsorization process for this variable will be conducted at that time. Then, for the left-skewed ratio variables, a square root transformation was applied to moderate the spread of values while maintaining interpretability. Conversely, a logarithmic transformation was used for the right-skewed variables to normalize their distribution (West 2022) (see Appendix E). Since the "roa_w" variable is left skewed a square root transformation has been performed. Since for a square root transformation the values need to be strictly positive, the variable is shifted by +0.064, which offsets its minimum value of -0.06325. Next to adjust for the negatively skewedness of the “roe” variable, the square root of the variable is taken (Biostats 2017). The variable is shifted by +0.816 to be strictly positive. The same procedure is applied to the variables “npm_w”, “gpm_w”, “debt_at_w” and “de_ratio_w”. The variables “revt_w” and “at_w” exhibit a high degree of right skewedness and positive values. Consequently a logarithmic transformation was performed on these variables (West 2022). The variable 'ebit_w' has a minimum value of -3,357,000; therefore, a shift of +3,357,000.001 was applied to the variable before performing the logarithmic transformation. These adjustments allow for a more accurate and meaningful analysis of the dataset.

**Short-Term Data**

For the short-term analysis, a slightly modified dataset is used, which includes the average abnormal return as well as the cumulative abnormal return as additional variables. Since tests have already been performed for all other variables, this section focuses exclusively on tests related to abnormal returns. The tests performed include a normality test, tests for heteroscedasticity and autocorrelation as well as a test for multicollinearity.

To assess normality histograms were plotted (Figure 11), and the Shapiro-Wilk test was applied to both abnormal return variables. The resulting p-values of 0.000 as well as the plotted graph indicate a significant deviation from normality in the abnormal returns.

**Figure 11: Histograms of Abnormal Returns**




To assess the presence of heteroscedasticity, the Breusch-Pagan test was performed. The significant p-values of 0.000 for both abnormal return variables led to the rejection of the null hypothesis, indicating heteroscedasticity in the data. To address this, robust standard errors are used in the following analyses. Finally, a test for multicollinearity is performed to determine which variables may need to be excluded from the model. This assessment is carried out using the VIF. As seen in Table 14 all values are below five, proving that there is no multicollinearity between the independent variables (Daoud 2017).

**Table 14: VIF-Test for Multicollinearity (short-term)**

| Variable | vif | 1/vif |
|---|---|---|
| EBIT | 4.33 | 0.2310 |
| Revenue | 4.26 | 0.2347 |
| Asset value | 1.97 | 0.5082 |
| Net profit margin | 1.93 | 0.5172 |
| Gross profit margin | 1.89 | 0.5302 |
| Return on assets | 1.81 | 0.5534 |

| | | |
|---|---|---|
| Debt-to-assets ratio | 1.25 | 0.7994 |
| Return on Equity | 1.06 | 0.9444 |
| Penalty Amount per date | 1.00 | 0.9976 |
| Debt-to-equity ratio | 1.00 | 0.9986 |
| **Mean vif** | **2.05** | |

Lastly, the short-term data must also be adjusted for outliers in the same manner as described above with the winsorization method. After this adjustment, the skewness test on the variables "mean_aret_w" and "car_w" shows that the p-values are not significant ($p = 0.5689$ and $p = 0.2742$) at the 10% significance level (Table 15). Therefore, the null hypothesis, which posits that the data is normally distributed, cannot be rejected. Consequently, no further adjustments are necessary to include this variable in the subsequent analysis.

**Table 15: Sktest for Normality on Abnormal Returns**

| | | | | **joint test** | |
|---|---|---|---|---|---|
| | **n** | **pr(skewness)** | **pr(kurtosis)** | **adj chi(2)** | **prob>chi2** |
| Mean abnormal return winsorized | 8,073 | 0.5689 | 0.0000 | 372.21 | 0.0000 |

| | | | | **joint test** | |
|---|---|---|---|---|---|
| | **n** | **pr(skewness)** | **pr(kurtosis)** | **adj chi(2)** | **prob>chi2** |
| Cum. abnormal return winsorized | 8,073 | 0.2742 | 0.0000 | 372.71 | 0.0000 |

**Appendix B: Hausmann Test**

| | **Chi2** | **Prob>chi2** |
|---|---|---|
| Test of H0: Difference in coefficients not systematic | 147.79 | 0.0000 |

**Appendix C: Wald Test**

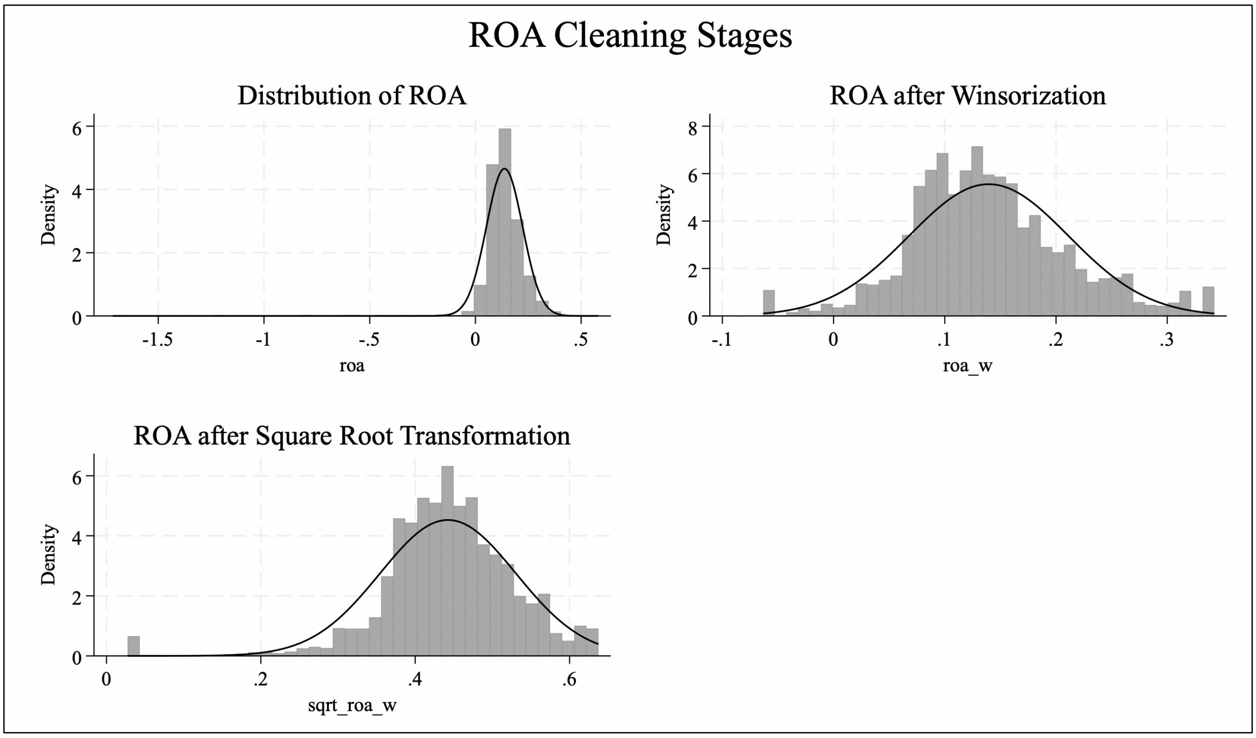
| | **Chi2 (711)** | **Prob>chi2** |
|---|---|---|

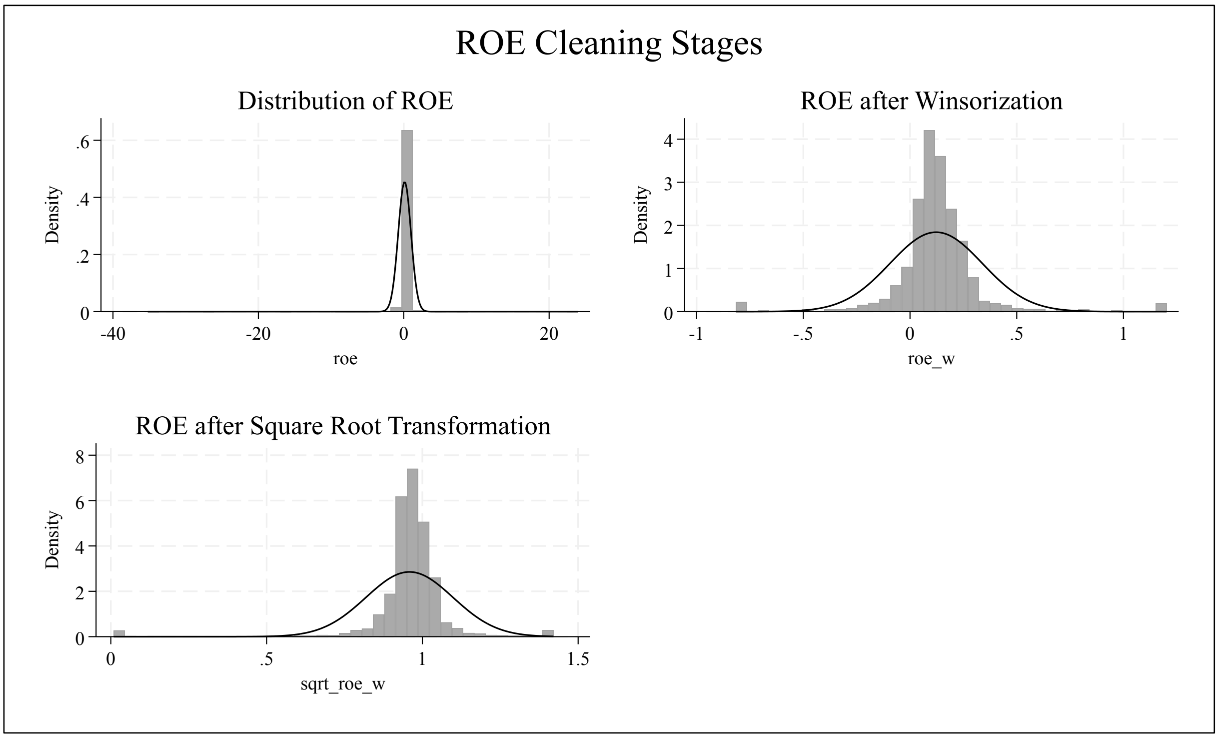
| | | |
|---|---|---|
| Test of H0: sigma (i)^2 = sigma ^2 for all i | 6.88e+38 | 0.0000 |

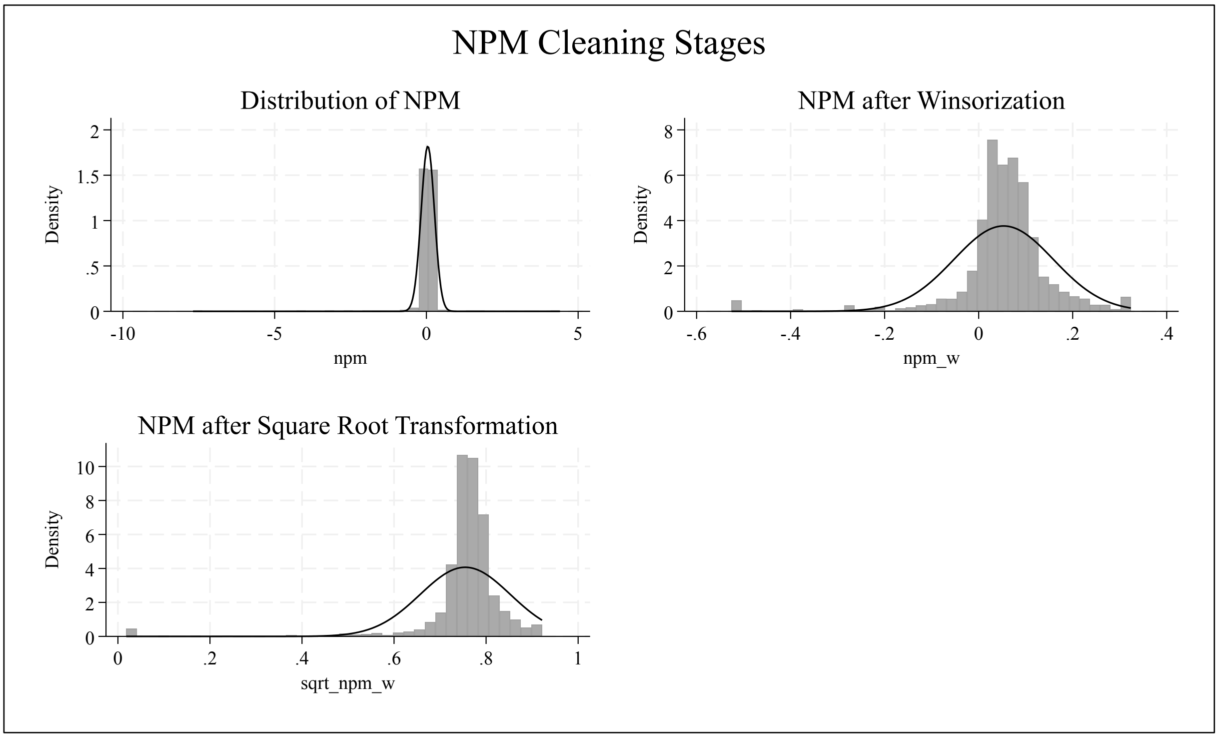
**Appendix D: Regression of Residuals on Lagged Values**

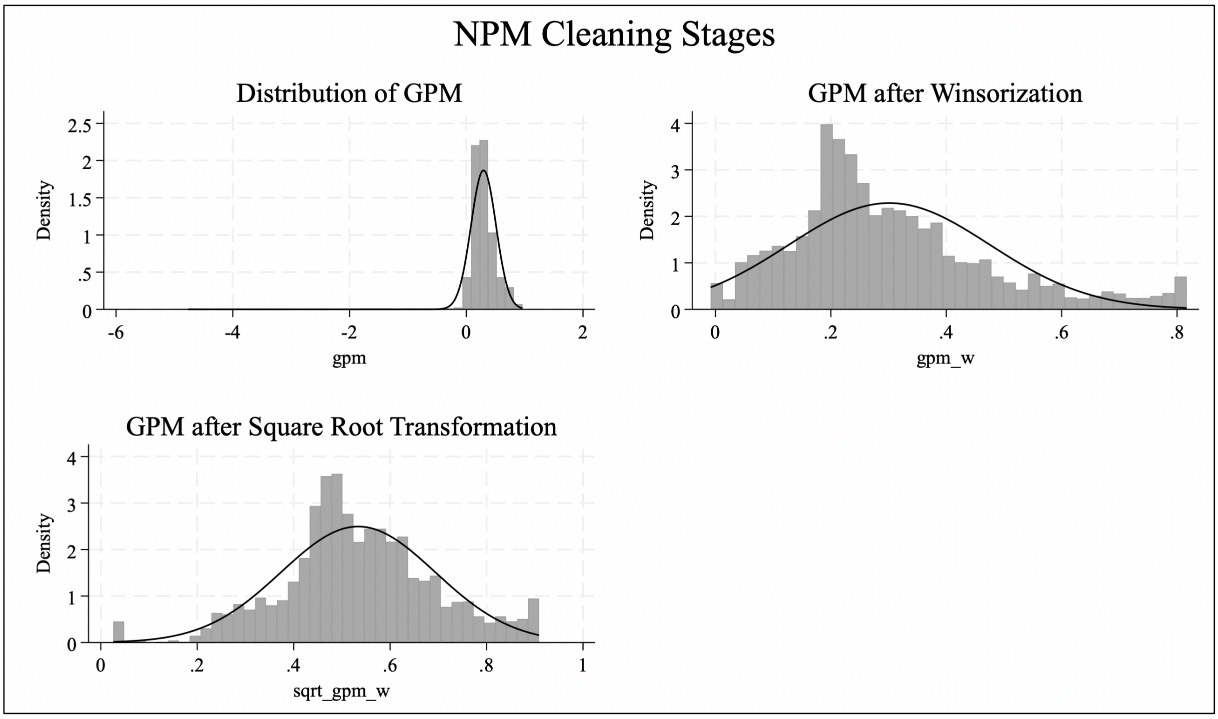
| residuals | **Coefficient** | **Std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
|---|---|---|---|---|---|---|
| lagged_residuals | 1.019866 | .0047764 | 213.52 | 0.000 | 1.010498 | 1.029233 |
| _cons | 77,140.74 | 214,099.9 | 0.36 | 0.719 | -342,753.6 | 497,035.1 |

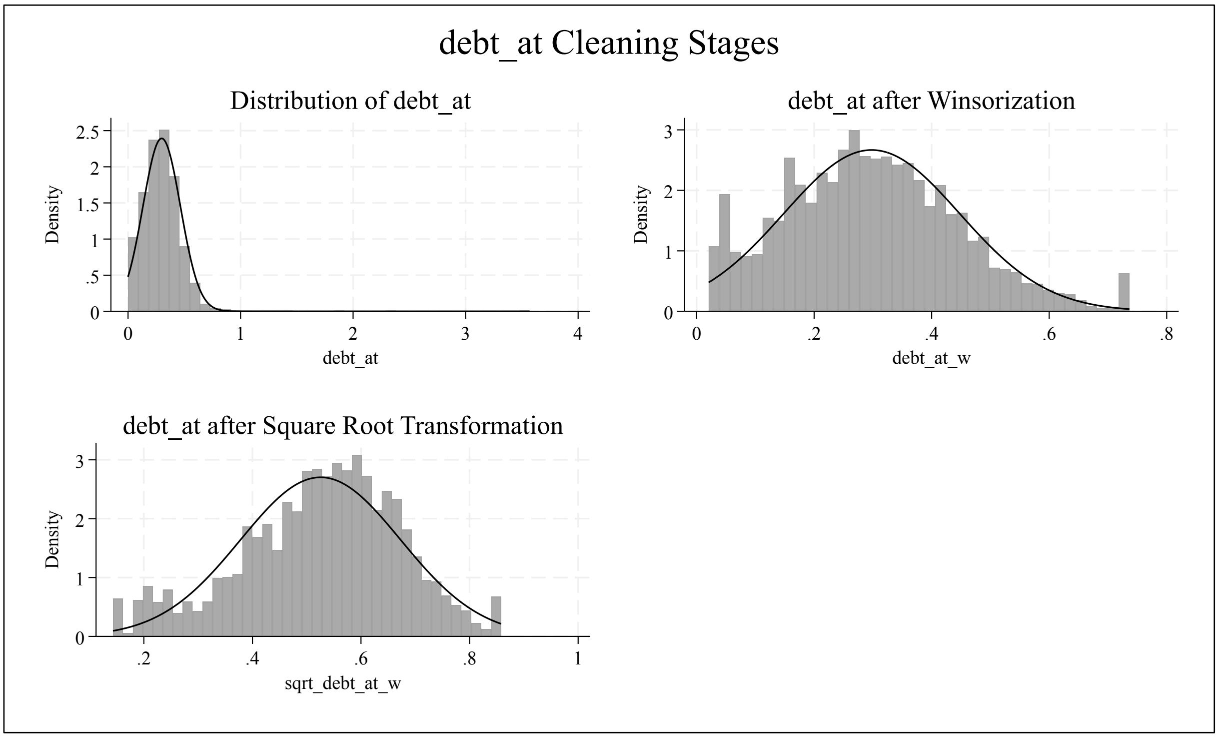
**Appendix E: Winsorization for all Variables**

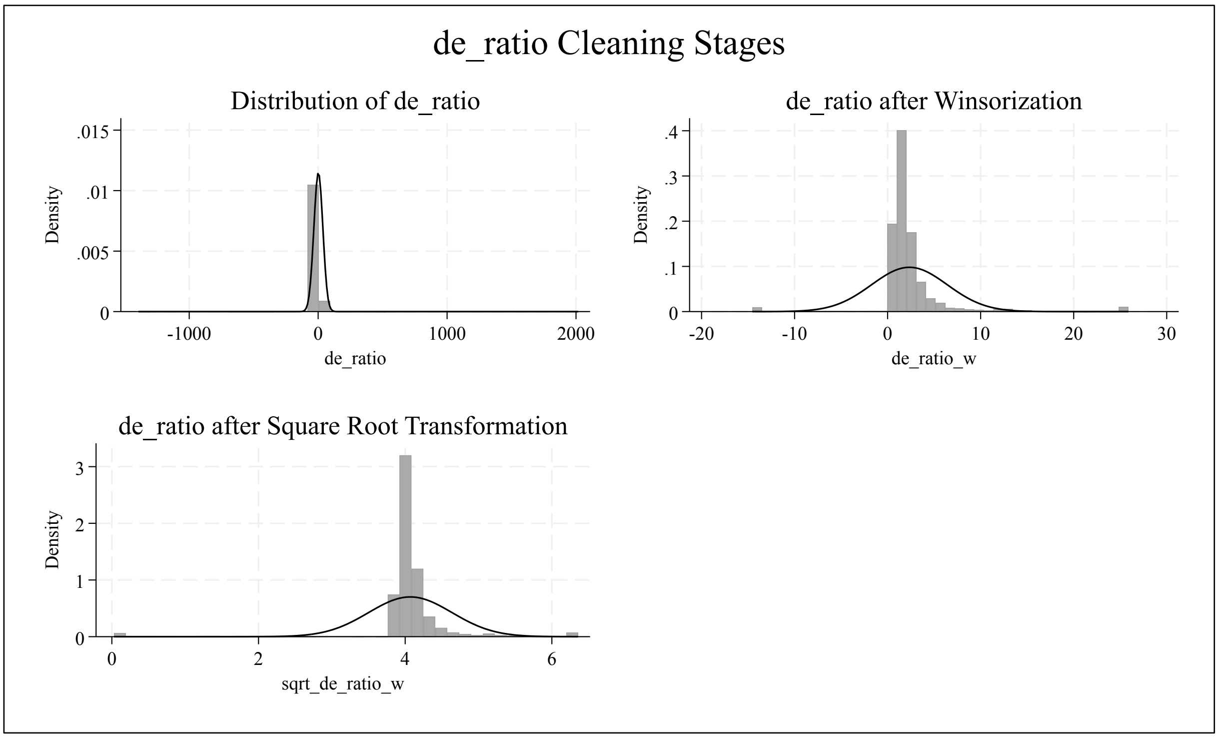


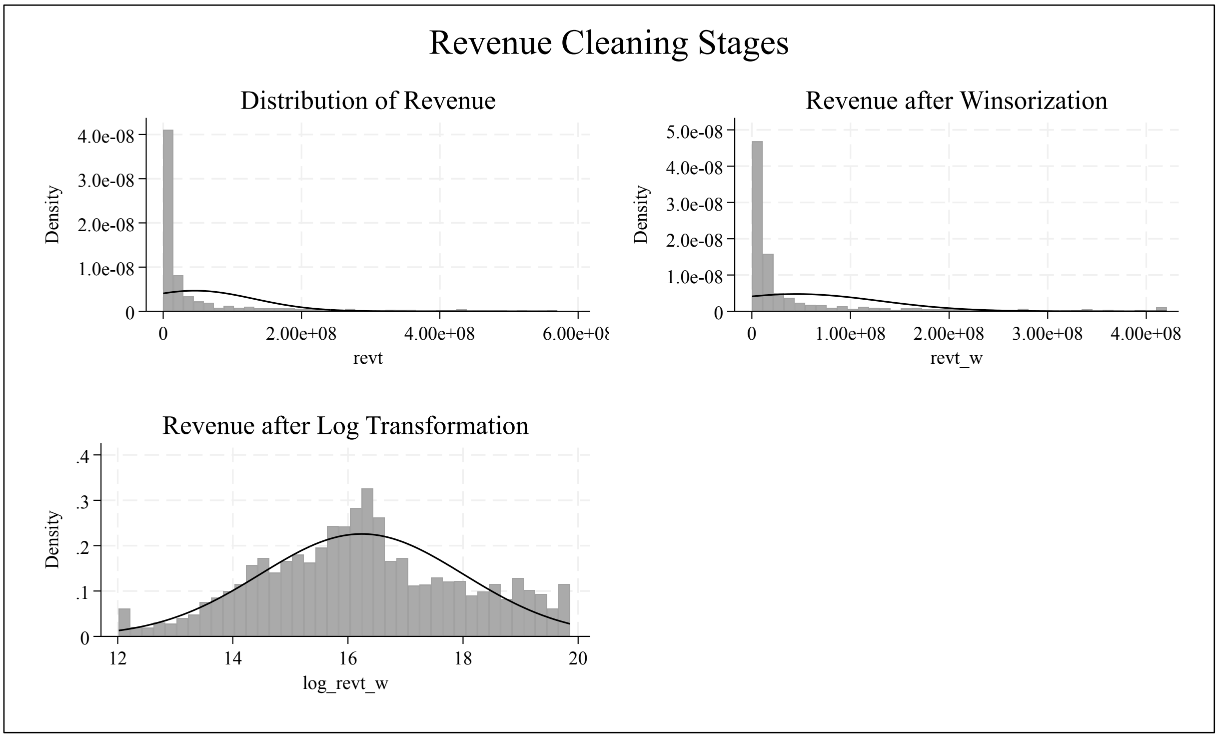

ROE Cleaning Stages
Distribution of ROE
Density
roe
ROE after Winsorization
roe_w
ROE after Square Root Transformation
sqrt_roe_w

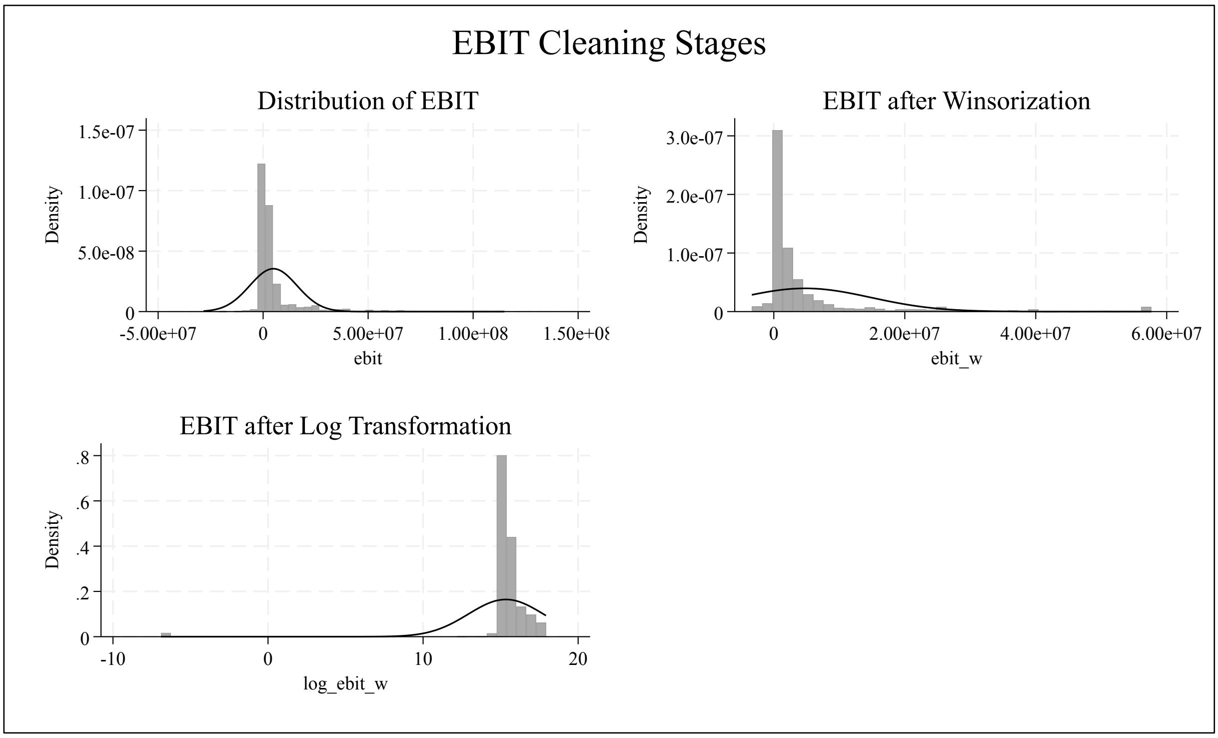

NPM Cleaning Stages
Distribution of NPM
Density
npm
NPM after Winsorization
npm_w
NPM after Square Root Transformation
sqrt_npm_w

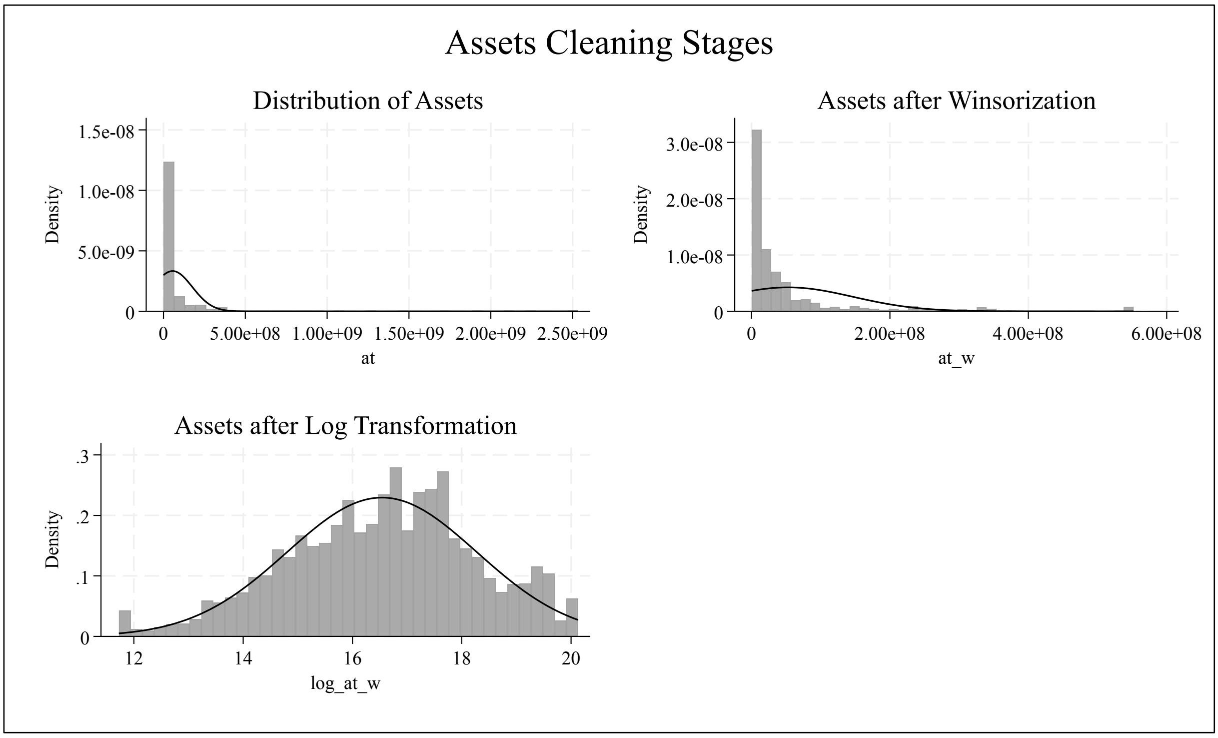

NPM Cleaning Stages
Distribution of GPM
Density
gpm
GPM after Winsorization
gpm_w
GPM after Square Root Transformation
sqrt_gpm_w


debt_at Cleaning Stages
Distribution of debt_at
Density
debt_at
debt_at after Winsorization
debt_at_w
debt_at after Square Root Transformation
sqrt_debt_at_w


de_ratio Cleaning Stages
Distribution of de_ratio
Density
.015
.01
.005
0
-1000
0
1000
2000
de_ratio
de_ratio after Winsorization
Density
.4
.3
.2
.1
0
-20
-10
0
10
20
30
de_ratio_w
de_ratio after Square Root Transformation
Density
3
2
1
0
0
2
4
6
sqrt_de_ratio_w


Revenue Cleaning Stages
Distribution of Revenue
Density
4.0e-08
3.0e-08
2.0e-08
1.0e-08
0
0
2.00e+08
4.00e+08
revt
Revenue after Winsorization
Density
5.0e-08
4.0e-08
3.0e-08
2.0e-08
1.0e-08
0
0
1.00e+08
2.00e+08
3.00e+08
4.00e+08
revt_w
Revenue after Log Transformation
Density
.4
.3
.2
.1
0
12
14
16
18
20
log_revt_w




## Appendix F: Sample Descriptives of Long-Term Dataset

| | | |
|---|---|---|
| observations | 9,579 | |
| variables | 41 | |
| **Variable** | **storage type** | **display format** |
| year | int | %10.0g |

| | | |
|---|---|---|
| penalty_date | long | %12.0g |
| parentcompany | str61 | %61s |
| penalty_not_standardized | double | %10.0g |
| primary_offense | str53 | %53s |
| reporting_date_parent | str61 | %61s |
| tic | str8 | %9s |
| debt_assets | float | %9.0g |
| staff_sale | float | %9.0g |
| roa | float | %9.0g |
| roe | float | %9.0g |
| npm | float | %9.0g |
| gpm | float | %9.0g |
| debt_at | float | %9.0g |
| de_ratio | float | %9.0g |
| naics | long | %12.0g |
| revt | float | %9.0g |
| at | float | %9.0g |
| ebit | float | %9.0g |
| name | str55 | %55s |
| total_grade | str3 | %9s |
| total_level | str6 | %9s |
| penalty | float | %9.0g |
| roa_w | float | %9.0g |
| sqrt_roa_w | float | %9.0g |
| npm_w | float | %9.0g |
| sqrt_npm_w | float | %9.0g |
| gpm_w | float | %9.0g |
| sqrt_gpm_w | float | %9.0g |
| debt_at_w | float | %9.0g |
| sqrt_debt_at_w | float | %9.0g |
| de_ratio_w | float | %9.0g |
| sqrt_de_ratio_w | float | %9.0g |
| revt_w | float | %9.0g |
| log_revt_w | float | %9.0g |
| ebit_w | float | %9.0g |
| log_ebit_w | float | %9.0g |
| at_w | float | %9.0g |
| log_at_w | float | %9.0g |

### Appendix G: Company Size Overview of long-term Dataset

| | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Asset value** | 9,541 | 5,2800,000 | 93,800,000 | 123,662 | 5.523e+08 |

| | N | p1 | p99 | Skew. | Kurt. |
|---|---|---|---|---|---|
| **Asset value** | 9,541 | 164,103 | 5.523e+08 | 3.087 | 13.564 |

### Appendix H: Company's ESG Score within long-term Dataset

| Total grade | Freq. | Percent | Cum. |
|---|---|---|---|
| A | 53 | 20.31 | 20.31 |
| B | 36 | 13.79 | 34.10 |
| BB | 19 | 7.28 | 41.38 |
| BBB | 153 | 58.62 | 100.00 |
| **Total** | **261** | **100.00** | |

### Appendix I: Fixed Effect Panel Regression Output (Entire Sample)

| log_revt_w | Coefficient | std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | -.020537 | .0048406 | -4.24 | 0.000 | -.0300386 | -.0110354 |
| **year** | | | | | | |
| 2001 | .083345 | .0408505 | 2.04 | 0.042 | .0031595 | .1635305 |
| 2002 | .0447695 | .0501571 | 0.89 | 0.372 | -.0536838 | .1432229 |
| 2003 | .2019949 | .050533 | 4.00 | 0.000 | .1028036 | .3011862 |
| 2004 | .2677777 | .0525842 | 5.09 | 0.000 | .1645603 | .3709952 |
| 2005 | .418779 | .0495493 | 8.45 | 0.000 | .3215187 | .5160393 |
| 2006 | .5078809 | .0515266 | 9.86 | 0.000 | .4067393 | .6090224 |
| 2007 | .5801272 | .0568232 | 10.21 | 0.000 | .468589 | .6916655 |
| 2008 | .6333929 | .0624042 | 10.15 | 0.000 | .5108997 | .755886 |
| 2009 | .4613876 | .0588556 | 7.84 | 0.000 | .3458598 | .5769154 |
| 2010 | .5606781 | .0653611 | 8.58 | 0.000 | .4323808 | .6889755 |
| 2011 | .7015892 | .064176 | 10.93 | 0.000 | .5756181 | .8275602 |
| 2012 | .7458336 | .0642908 | 11.60 | 0.000 | .6196372 | .87203 |
| 2013 | .7511158 | .062518 | 12.01 | 0.000 | .6283992 | .8738324 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2014 | .8457113 | .0648561 | 13.04 | 0.000 | .7184052 | .9730173 |
| 2015 | .6973255 | .0641322 | 10.87 | 0.000 | .5714404 | .8232106 |
| 2016 | .667588 | .0679621 | 9.82 | 0.000 | .5341852 | .8009908 |
| 2017 | .7685121 | .068075 | 11.29 | 0.000 | .6348876 | .9021366 |
| 2018 | .8922396 | .0651749 | 13.69 | 0.000 | .7643078 | 1.020171 |
| 2019 | .9022134 | .0653505 | 13.81 | 0.000 | .773937 | 1.03049 |
| 2020 | .8206519 | .0715963 | 11.46 | 0.000 | .6801155 | .9611882 |
| 2021 | 1.05357 | .0753923 | 13.97 | 0.000 | .9055824 | 1.201558 |
| 2022 | 1.206801 | .0801783 | 15.05 | 0.000 | 1.049419 | 1.364183 |
| | | | | | | |
| _cons | 14.78639 | .078873 | 187.47 | 0.000 | 14.63157 | 14.94121 |

| **log_revt_w** | **Coefficient** | **Robust std. err.** | **t** | **P>\|t\|** | **[95% conf.** | **interval]** |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | -.0147251 | .0039161 | -3.76 | 0.000 | -.0224139 | -.0070364 |
| log_ebit_w | .022263 | .0061092 | 3.64 | 0.000 | .0102684 | .0342577 |
| sqrt_debt_at_w | .3108067 | .1791617 | 1.73 | 0.083 | -.0409556 | .662569 |
| sqrt_gpm_w | -1.439531 | .3600547 | -4.00 | 0.000 | -2.146455 | -.7326076 |
| sqrt_npm_w | .2180178 | .2208236 | 0.99 | 0.324 | -.2155425 | .6515781 |
| sqrt_roa_w | 2.085744 | .4438095 | 4.70 | 0.000 | 1.214378 | 2.95711 |
| sqrt_roe_w | .0719507 | .0978944 | 0.73 | 0.463 | -.1202532 | .2641545 |
| | | | | | | |
| **year** | | | | | | |
| 2001 | .04938 | .0437304 | 1.13 | 0.259 | -.0364792 | .1352393 |
| 2002 | .0805757 | .0491446 | 1.64 | 0.102 | -.0159138 | .1770652 |
| 2003 | .2218307 | .0521594 | 4.25 | 0.000 | .119422 | .3242394 |
| 2004 | .2945886 | .0509917 | 5.78 | 0.000 | .1944725 | .3947046 |
| 2005 | .3989434 | .049417 | 8.07 | 0.000 | .3019192 | .4959676 |
| 2006 | .4780393 | .0509622 | 9.38 | 0.000 | .3779812 | .5780974 |
| 2007 | .5719511 | .0547849 | 10.44 | 0.000 | .4643875 | .6795146 |
| 2008 | .6431114 | .0568062 | 11.32 | 0.000 | .5315793 | .7546435 |
| 2009 | .4999039 | .057272 | 8.73 | 0.000 | .3874573 | .6123506 |
| 2010 | .6220386 | .063974 | 9.72 | 0.000 | .4964334 | .7476439 |
| 2011 | .7086313 | .0609973 | 11.62 | 0.000 | .5888706 | .828392 |
| 2012 | .7341574 | .0630753 | 11.64 | 0.000 | .6103166 | .8579981 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2013 | .7693953 | .0624947 | 12.31 | 0.000 | .6466946 | .892096 |
| 2014 | .8739823 | .0637891 | 13.70 | 0.000 | .7487401 | .9992244 |
| 2015 | .758386 | .061604 | 12.31 | 0.000 | .637434 | .8793381 |
| 2016 | .7457262 | .0653408 | 11.41 | 0.000 | .6174374 | .874015 |
| 2017 | .8338222 | .0685281 | 12.17 | 0.000 | .6992757 | .9683688 |
| 2018 | .9048474 | .0672326 | 13.46 | 0.000 | .7728443 | 1.03685 |
| 2019 | .8970913 | .0664197 | 13.51 | 0.000 | .7666844 | 1.027498 |
| 2020 | .8855541 | .072232 | 12.26 | 0.000 | .7437354 | 1.027373 |
| 2021 | 1.067856 | .0770038 | 13.87 | 0.000 | .9166688 | 1.219044 |
| 2022 | 1.187322 | .0803561 | 14.78 | 0.000 | 1.029552 | 1.345091 |
| | | | | | | |
| _cons | 14.07302 | .1984644 | 70.91 | 0.000 | 13.68336 | 14.46268 |

| **log_ebit_w** | **Coefficient** | **std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | .0365119 | .0263846 | 1.38 | 0.167 | -.0152783 | .0883021 |
| | | | | | | |
| **year** | | | | | | |
| 2001 | .019189 | .0735162 | 0.26 | 0.794 | -.1251156 | .1634937 |
| 2002 | -.0281093 | .0651716 | -0.43 | 0.666 | -.1560343 | .0998158 |
| 2003 | -.0016506 | .0599824 | -0.03 | 0.978 | -.1193899 | .1160887 |
| 2004 | .1291449 | .0661016 | 1.95 | 0.051 | -.0006057 | .2588956 |
| 2005 | -.031961 | .1658289 | -0.19 | 0.847 | -.357466 | .293544 |
| 2006 | -.0303948 | .154035 | -0.20 | 0.844 | -.3327497 | .2719601 |
| 2007 | .1113616 | .0776122 | 1.43 | 0.152 | -.0409833 | .2637064 |
| 2008 | -.283027 | .2146278 | -1.32 | 0.188 | -.7043192 | .1382651 |
| 2009 | -.2241758 | .1877839 | -1.19 | 0.233 | -.5927762 | .1444246 |
| 2010 | .0644204 | .0638816 | 1.01 | 0.314 | -.0609726 | .1898134 |
| 2011 | .1436382 | .0581826 | 2.47 | 0.014 | .0294317 | .2578447 |
| 2012 | .0055269 | .1330305 | 0.04 | 0.967 | -.2555982 | .266652 |
| 2013 | .1414363 | .0629636 | 2.25 | 0.025 | .0178452 | .2650274 |
| 2014 | .1257821 | .0637859 | 1.97 | 0.049 | .000577 | .2509872 |
| 2015 | -1.254583 | .380135 | -3.30 | 0.001 | -2.000749 | -.508417 |
| 2016 | -.3223774 | .2098292 | -1.54 | 0.125 | -.7342504 | .0894957 |
| 2017 | -.0341535 | .1398198 | -0.24 | 0.807 | -.3086053 | .2402983 |
| 2018 | .1215905 | .0744784 | 1.63 | 0.103 | -.0246029 | .267784 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2019 | .0741011 | .0775525 | 0.96 | 0.340 | -.0781265 | .2263287 |
| 2020 | -1.023558 | .3743212 | -2.73 | 0.006 | -1.758312 | -.288804 |
| 2021 | .2397003 | .0944309 | 2.54 | 0.011 | .0543422 | .4250585 |
| 2022 | -.0994192 | .2234221 | -0.44 | 0.656 | -.5379738 | .3391354 |
| | | | | | | |
| _cons | 15.75589 | .3219008 | 48.95 | 0.000 | 15.12403 | 16.38775 |

| **log_ebit_w** | **Coefficient** | **Robust std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | .0420119 | .0282362 | 1.49 | 0.137 | -.0134262 | .09745 |
| sqrt_debt_at_w | .9820304 | .5125569 | 1.92 | 0.056 | -.0243101 | 1.988371 |
| sqrt_gpm_w | .7844926 | 1.499469 | 0.52 | 0.601 | -2.159524 | 3.72851 |
| sqrt_npm_w | 2.817274 | 1.730276 | 1.63 | 0.104 | -.5799031 | 6.214451 |
| sqrt_roa_w | 2.780757 | 1.574895 | 1.77 | 0.078 | -.3113499 | 5.872865 |
| sqrt_roe_w | .3646626 | 1.0649 | 0.34 | 0.732 | -1.726134 | 2.455459 |
| | | | | | | |
| **year** | | | | | | |
| 2001 | .0701691 | .0697991 | 1.01 | 0.315 | -.0668726 | .2072108 |
| 2002 | .1381073 | .0988011 | 1.40 | 0.163 | -.0558761 | .3320907 |
| 2003 | .241606 | .1096647 | 2.20 | 0.028 | .0262932 | .4569188 |
| 2004 | .2584534 | .0959232 | 2.69 | 0.007 | .0701204 | .4467864 |
| 2005 | .1624513 | .0949683 | 1.71 | 0.088 | -.0240069 | .3489095 |
| 2006 | .0016336 | .2068642 | 0.01 | 0.994 | -.4045181 | .4077854 |
| 2007 | .1649881 | .1058775 | 1.56 | 0.120 | -.042889 | .3728652 |
| 2008 | -.2618375 | .2660464 | -0.98 | 0.325 | -.7841858 | .2605109 |
| 2009 | .1510703 | .1232157 | 1.23 | 0.221 | -.0908481 | .3929888 |
| 2010 | .2822299 | .1210857 | 2.33 | 0.020 | .0444936 | .5199663 |
| 2011 | .2484846 | .0976051 | 2.55 | 0.011 | .0568493 | .4401199 |
| 2012 | .2114243 | .1109001 | 1.91 | 0.057 | -.006314 | .4291626 |
| 2013 | .2801794 | .1132567 | 2.47 | 0.014 | .0578142 | .5025446 |
| 2014 | .22915 | .1049276 | 2.18 | 0.029 | .023138 | .435162 |
| 2015 | -1.046246 | .3581823 | -2.92 | 0.004 | -1.749491 | -.3430002 |
| 2016 | -.0388263 | .1705277 | -0.23 | 0.820 | -.3736358 | .2959833 |
| 2017 | .1980465 | .1483659 | 1.33 | 0.182 | -.0932511 | .4893441 |
| 2018 | .1925316 | .0953893 | 2.02 | 0.044 | .0052468 | .3798164 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2019 | .1510989 | .1216741 | 1.24 | 0.215 | -.0877928 | .3899906 |
| 2020 | -.7715395 | .3820813 | -2.02 | 0.044 | -1.521708 | -.0213713 |
| 2021 | .5090156 | .1560545 | 3.26 | 0.001 | .2026225 | .8154088 |
| 2022 | .2598875 | .1362734 | 1.91 | 0.057 | -.007668 | .5274431 |
| | | | | | | |
| _cons | 11.0391 | 1.164948 | 9.48 | 0.000 | 8.751869 | 13.32632 |

## Appendix J: Event Study Regression Output (Entire Sample)

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | .0000399 | .0000551 | 0.72 | 0.469 | -.0000681 | .0001479 |
| _cons | .0002596 | .0007393 | 0.35 | 0.725 | -.0011896 | .0017087 |

| mean_aret_w | Coefficient | std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | 8.79e-06 | .0000669 | 0.13 | 0.895 | -.0001224 | .00014 |
| log_revt_w | -.0001048 | .0000992 | -1.06 | 0.291 | -.0002992 | .0000897 |
| log_ebit_w | .000058 | .0000933 | 0.62 | 0.534 | -.0001249 | .0002409 |
| sqrt_de_ratio_w | .0000775 | .0003091 | 0.25 | 0.802 | -.0005283 | .0006834 |
| sqrt_gpm_w | -.0005063 | .0010314 | -0.49 | 0.624 | -.0025282 | .0015157 |
| sqrt_npm_w | .0022094 | .0025747 | 0.86 | 0.391 | -.0028378 | .0072567 |
| sqrt_roa_w | .0012481 | .002236 | 0.56 | 0.577 | -.0031352 | .0056313 |
| sqrt_roe_w | -.0021871 | .0017493 | -1.25 | 0.211 | -.0056164 | .0012421 |
| _cons | .0004823 | .0025289 | 0.19 | 0.849 | -.0044751 | .0054398 |

| car_winsor | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | .0001195 | .0001658 | 0.72 | 0.471 | -.0002055 | .0004445 |
| _cons | .0007599 | .002226 | 0.34 | 0.733 | -.0036037 | .0051235 |

| car_winsor | Coefficient | std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | .0000307 | .0002018 | 0.15 | 0.879 | -.0003649 | .0004263 |

| | | | | | | |
|---|---|---|---|---|---|---|
| log_revt_w | -.0003019 | .0002995 | -1.01 | 0.313 | -.000889 | .0002852 |
| log_ebit_w | .0001751 | .00028 | 0.63 | 0.532 | -.0003738 | .000724 |
| sqrt_de_ratio_w | .0002358 | .000928 | 0.25 | 0.799 | -.0015833 | .0020549 |
| sqrt_gpm_w | -.0014656 | .0031038 | -0.47 | 0.637 | -.0075501 | .0046188 |
| sqrt_npm_w | .0065105 | .0077374 | 0.84 | 0.400 | -.0086572 | .0216783 |
| sqrt_roa_w | .0034647 | .0067523 | 0.51 | 0.608 | -.0097717 | .0167012 |
| sqrt_roe_w | -.0064957 | .0052523 | -1.24 | 0.216 | -.0167918 | .0038004 |
| _cons | .0013772 | .0076002 | 0.18 | 0.856 | -.0135214 | .0162758 |

**Appendix K: Fixed Effect Panel Regression Output (Air Pollution)**

| **log_revt_w** | **Coefficient** | **Robust std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
|---|---|---|---|---|---|---|
| log_total_penalty_vtype_w | -.0261551 | .0076916 | -3.40 | 0.001 | -.0412812 | -.0110291 |
| log_ebit_w | .0195784 | .0043044 | 4.55 | 0.000 | .0111136 | .0280431 |
| sqrt_debt_at_w | .4841329 | .2953167 | 1.64 | 0.102 | -.0966242 | 1.06489 |
| sqrt_gpm_w | -.7504893 | .5088148 | -1.47 | 0.141 | -1.751103 | .2501241 |
| sqrt_npm_w | -.0897811 | .2628227 | -0.34 | 0.733 | -.6066368 | .4270747 |
| sqrt_roa_w | 1.661767 | .6757493 | 2.46 | 0.014 | .3328674 | 2.990667 |
| sqrt_roe_w | .0440784 | .1207645 | 0.36 | 0.715 | -.1934118 | .2815687 |
| | | | | | | |
| **year** | | | | | | |
| 2001 | -.0003114 | .1081503 | -0.00 | 0.998 | -.2129952 | .2123724 |
| 2002 | .0876737 | .1023874 | 0.86 | 0.392 | -.113677 | .2890244 |
| 2003 | .2405645 | .0983776 | 2.45 | 0.015 | .0470994 | .4340297 |
| 2004 | .3464926 | .1040591 | 3.33 | 0.001 | .1418544 | .5511309 |
| 2005 | .3723503 | .0983383 | 3.79 | 0.000 | .1789625 | .5657381 |
| 2006 | .5522193 | .1098176 | 5.03 | 0.000 | .3362566 | .7681819 |
| 2007 | .5690235 | .1122665 | 5.07 | 0.000 | .348245 | .789802 |
| 2008 | .683213 | .1244489 | 5.49 | 0.000 | .4384771 | .9279488 |
| 2009 | .4836618 | .1160625 | 4.17 | 0.000 | .2554183 | .7119053 |
| 2010 | .639145 | .1288467 | 4.96 | 0.000 | .3857606 | .8925294 |
| 2011 | .7602072 | .1374639 | 5.53 | 0.000 | .4898766 | 1.030538 |
| 2012 | .7369364 | .13181 | 5.59 | 0.000 | .4777246 | .9961482 |
| 2013 | .7671147 | .1333546 | 5.75 | 0.000 | .5048652 | 1.029364 |
| 2014 | .8376959 | .1296572 | 6.46 | 0.000 | .5827176 | 1.092674 |
| 2015 | .7767814 | .1314497 | 5.91 | 0.000 | .5182781 | 1.035285 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2016 | .6811559 | .1356267 | 5.02 | 0.000 | .4144383 | .9478734 |
| 2017 | .803684 | .1413936 | 5.68 | 0.000 | .5256254 | 1.081743 |
| 2018 | .810552 | .1358685 | 5.97 | 0.000 | .5433587 | 1.077745 |
| 2019 | .8173134 | .1275861 | 6.41 | 0.000 | .566408 | 1.068219 |
| 2020 | .8326577 | .1398765 | 5.95 | 0.000 | .5575826 | 1.107733 |
| 2021 | .9891374 | .1440377 | 6.87 | 0.000 | .705879 | 1.272396 |
| 2022 | 1.190277 | .1627985 | 7.31 | 0.000 | .8701245 | 1.51043 |
| | | | | | | |
| _cons | 14.25507 | .3215098 | 44.34 | 0.000 | 13.6228 | 14.88734 |

| | | **Robust** | | | | |
|---|---|---|---|---|---|---|
| **log_ebit_w** | **Coefficient** | **std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
| log_total_penalty_vtype_w | .0360975 | .0297949 | 1.21 | 0.226 | -.0224958 | .0946909 |
| log_revt_w | .8271122 | .2780066 | 2.98 | 0.003 | .2803964 | 1.373828 |
| sqrt_debt_at_w | .2304194 | .9926155 | 0.23 | 0.817 | -1.721616 | 2.182455 |
| sqrt_gpm_w | 3.091551 | 2.452993 | 1.26 | 0.208 | -1.7324 | 7.915501 |
| sqrt_npm_w | .7817058 | 1.962164 | 0.40 | 0.691 | -3.077002 | 4.640413 |
| sqrt_roa_w | -1.008211 | 2.592268 | -0.39 | 0.698 | -6.106053 | 4.089632 |
| sqrt_roe_w | 3.071409 | 2.106738 | 1.46 | 0.146 | -1.071611 | 7.214429 |
| | | | | | | |
| **year** | | | | | | |
| 2001 | .5880177 | .3735237 | 1.57 | 0.116 | -.1465379 | 1.322573 |
| 2002 | -.1480442 | .1705015 | -0.87 | 0.386 | -.4833451 | .1872568 |
| 2003 | .3087955 | .3087112 | 1.00 | 0.318 | -.2983028 | .9158938 |
| 2004 | -.1927573 | .1723163 | -1.12 | 0.264 | -.5316272 | .1461125 |
| 2005 | -.2302956 | .2112516 | -1.09 | 0.276 | -.6457338 | .1851427 |
| 2006 | -.5921787 | .4639624 | -1.28 | 0.203 | -1.504587 | .3202299 |
| 2007 | -.0742023 | .3225243 | -0.23 | 0.818 | -.7084646 | .5600601 |
| 2008 | -.9034199 | .4561979 | -1.98 | 0.048 | -1.800559 | -.0062807 |
| 2009 | -.0130149 | .2010913 | -0.06 | 0.948 | -.4084724 | .3824425 |
| 2010 | -.3662307 | .23175 | -1.58 | 0.115 | -.8219802 | .0895188 |
| 2011 | -.3549216 | .2318822 | -1.53 | 0.127 | -.8109312 | .101088 |
| 2012 | -.3211028 | .3172395 | -1.01 | 0.312 | -.9449723 | .3027668 |
| 2013 | -.3430881 | .2280777 | -1.50 | 0.133 | -.7916158 | .1054397 |
| 2014 | -.228426 | .3132073 | -0.73 | 0.466 | -.844366 | .387514 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2015 | -2.119584 | .8960451 | -2.37 | 0.019 | -3.881708 | -.3574606 |
| 2016 | -.3639653 | .2451793 | -1.48 | 0.139 | -.8461244 | .1181939 |
| 2017 | -.3671562 | .2511415 | -1.46 | 0.145 | -.8610403 | .1267278 |
| 2018 | -.6236257 | .2565242 | -2.43 | 0.016 | -1.128095 | -.1191562 |
| 2019 | -.6750526 | .2877557 | -2.35 | 0.020 | -1.240941 | -.1091646 |
| 2020 | -2.072815 | .8634224 | -2.40 | 0.017 | -3.770784 | -.3748453 |
| 2021 | -.4680354 | .283802 | -1.65 | 0.100 | -1.026148 | .0900775 |
| 2022 | -.694065 | .3763922 | -1.84 | 0.066 | -1.434262 | .0461317 |
| | | | | | | |
| _cons | -1.970358 | 4.748873 | -0.41 | 0.678 | -11.30929 | 7.368572 |

## Appendix L: Fixed Effect Panel Regression Output (Water Pollution)

| log_revt_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| log_total_penalty_vtype_w | -.0056237 | .0087616 | -0.64 | 0.522 | -.0229397 | .0116923 |
| log_ebit_w | .018916 | .0157129 | 1.20 | 0.231 | -.0121381 | .0499701 |
| sqrt_debt_at_w | .4638147 | .508849 | 0.91 | 0.364 | -.5418469 | 1.469476 |
| sqrt_gpm_w | -.9265826 | 1.039831 | -0.89 | 0.374 | -2.981648 | 1.128483 |
| sqrt_npm_w | -3.148756 | 1.50887 | -2.09 | 0.039 | -6.130805 | -.166708 |
| sqrt_roa_w | 4.037178 | 1.331842 | 3.03 | 0.003 | 1.404997 | 6.669359 |
| sqrt_roe_w | .566031 | .6420287 | 0.88 | 0.379 | -.7028397 | 1.834902 |
| | | | | | | |
| **year** | | | | | | |
| 2001 | -.385363 | .1615218 | -2.39 | 0.018 | -.704586 | -.06614 |
| 2002 | -.2950452 | .1800202 | -1.64 | 0.103 | -.6508274 | .060737 |
| 2003 | -.3381008 | .1771466 | -1.91 | 0.058 | -.6882038 | .0120021 |
| 2004 | -.0591099 | .1792806 | -0.33 | 0.742 | -.4134305 | .2952106 |
| 2005 | -.132195 | .1801084 | -0.73 | 0.464 | -.4881515 | .2237614 |
| 2006 | .1953573 | .2335343 | 0.84 | 0.404 | -.2661872 | .6569018 |
| 2007 | .156376 | .1629244 | 0.96 | 0.339 | -.1656191 | .478371 |
| 2008 | .1535618 | .1656969 | 0.93 | 0.356 | -.1739126 | .4810362 |
| 2009 | -.0416977 | .1833094 | -0.23 | 0.820 | -.4039805 | .3205851 |
| 2010 | .0501849 | .2199574 | 0.23 | 0.820 | -.3845269 | .4848967 |
| 2011 | .1755866 | .1859192 | 0.94 | 0.347 | -.1918541 | .5430272 |
| 2012 | .287667 | .2436656 | 1.18 | 0.240 | -.1939004 | .7692343 |
| 2013 | .2938964 | .1942531 | 1.51 | 0.132 | -.0900149 | .6778078 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2014 | .4701533 | .2170022 | 2.17 | 0.032 | .041282 | .8990245 |
| 2015 | .4096188 | .2044189 | 2.00 | 0.047 | .0056164 | .8136211 |
| 2016 | .5121929 | .2051125 | 2.50 | 0.014 | .1068196 | .9175661 |
| 2017 | .3006332 | .2072096 | 1.45 | 0.149 | -.1088846 | .7101509 |
| 2018 | .6739268 | .240943 | 2.80 | 0.006 | .1977401 | 1.150113 |
| 2019 | .420512 | .1959484 | 2.15 | 0.034 | .0332503 | .8077737 |
| 2020 | .4785824 | .2238304 | 2.14 | 0.034 | .0362162 | .9209485 |
| 2021 | .581325 | .2026194 | 2.87 | 0.005 | .1808791 | .9817709 |
| 2022 | 0 | (omitted) | | | | |
| | | | | | | |
| _cons | 15.70914 | .484028 | 32.46 | 0.000 | 14.75253 | 16.66574 |

| | | **Robust** | | | | |
|---|---|---|---|---|---|---|
| **log_ebit_w** | **Coefficient** | **std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
| log_total_penalty_vtype_w | .1351475 | .1227928 | 1.10 | 0.273 | -.1075335 | .3778284 |
| log_revt_w | .8182977 | .3672854 | 2.23 | 0.027 | .0924147 | 1.544181 |
| sqrt_debt_at_w | 4.506835 | 2.497082 | 1.80 | 0.073 | -.4282622 | 9.441931 |
| sqrt_gpm_w | 1.995038 | 2.314314 | 0.86 | 0.390 | -2.578846 | 6.568922 |
| sqrt_npm_w | 16.15445 | 8.99979 | 1.79 | 0.075 | -1.63225 | 33.94114 |
| sqrt_roa_w | 4.18346 | 4.020572 | 1.04 | 0.300 | -3.76258 | 12.1295 |
| sqrt_roe_w | -9.18044 | 4.046419 | -2.27 | 0.025 | -17.17756 | -1.183317 |
| | | | | | | |
| **year** | | | | | | |
| 2001 | .7693547 | .6661561 | 1.15 | 0.250 | -.5471999 | 2.085909 |
| 2002 | .5570668 | .4921857 | 1.13 | 0.260 | -.4156623 | 1.529796 |
| 2003 | .793485 | .6424209 | 1.24 | 0.219 | -.4761607 | 2.063131 |
| 2004 | 1.189183 | 1.080056 | 1.10 | 0.273 | -.9453811 | 3.323748 |
| 2005 | .7102844 | .5628376 | 1.26 | 0.209 | -.4020771 | 1.822646 |
| 2006 | .9582164 | .7010093 | 1.37 | 0.174 | -.4272204 | 2.343653 |
| 2007 | .3394733 | .5838384 | 0.58 | 0.562 | -.8143933 | 1.49334 |
| 2008 | .6999946 | .6479594 | 1.08 | 0.282 | -.580597 | 1.980586 |
| 2009 | -.5345873 | .7049237 | -0.76 | 0.449 | -1.92776 | .8585856 |
| 2010 | .7316671 | .6102448 | 1.20 | 0.232 | -.4743876 | 1.937722 |
| 2011 | .7970306 | .6538928 | 1.22 | 0.225 | -.4952877 | 2.089349 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2012 | .9150738 | .9124277 | 1.00 | 0.318 | -.8881988 | 2.718346 |
| 2013 | .0296379 | .6463311 | 0.05 | 0.963 | -1.247736 | 1.307012 |
| 2014 | 1.596331 | 1.159139 | 1.38 | 0.171 | -.6945287 | 3.887191 |
| 2015 | -1.541261 | 1.763851 | -0.87 | 0.384 | -5.027241 | 1.944718 |
| 2016 | .0537252 | .5268808 | 0.10 | 0.919 | -.9875734 | 1.095024 |
| 2017 | .6257105 | .6865763 | 0.91 | 0.364 | -.7312016 | 1.982623 |
| 2018 | .2555074 | .7286415 | 0.35 | 0.726 | -1.18454 | 1.695555 |
| 2019 | .078946 | .6274672 | 0.13 | 0.900 | -1.161146 | 1.319038 |
| 2020 | -.021767 | .5638139 | -0.04 | 0.969 | -1.136058 | 1.092524 |
| 2021 | 1.234221 | 1.472136 | 0.84 | 0.403 | -1.675227 | 4.14367 |
| 2022 | 0 | (omitted) | | | | |
| | | | | | | |
| _cons | -5.302943 | 8.377899 | -0.63 | 0.528 | -21.86057 | 11.25468 |

## Appendix M: Fixed Effect Panel Regression Output (Hazardous Waste Violations)

| log_revt_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_vtype_w | -.0283799 | .0145689 | -1.95 | 0.053 | -.0571267 | .0003668 |
| log_ebit_w | .00849 | .0082281 | 1.03 | 0.304 | -.0077453 | .0247253 |
| sqrt_debt_at_w | 1.139882 | .374139 | 3.05 | 0.003 | .401647 | 1.878117 |
| sqrt_gpm_w | -.4702362 | .8196679 | -0.57 | 0.567 | -2.08757 | 1.147097 |
| sqrt_npm_w | -1.6044 | 1.106027 | -1.45 | 0.149 | -3.786766 | .5779654 |
| sqrt_roa_w | -.5364104 | .7828947 | -0.69 | 0.494 | -2.081185 | 1.008364 |
| sqrt_roe_w | .4660858 | .2455313 | 1.90 | 0.059 | -.0183859 | .9505576 |
| | | | | | | |
| **year** | | | | | | |
| 2001 | -.1443161 | .1039374 | -1.39 | 0.167 | -.3494008 | .0607687 |
| 2002 | -.1308378 | .1552067 | -0.84 | 0.400 | -.4370851 | .1754094 |
| 2003 | .1128627 | .124362 | 0.91 | 0.365 | -.132523 | .3582485 |
| 2004 | -.2311785 | .2132192 | -1.08 | 0.280 | -.6518935 | .1895366 |
| 2005 | .2204505 | .1221994 | 1.80 | 0.073 | -.0206681 | .4615691 |
| 2006 | .4455045 | .0891404 | 5.00 | 0.000 | .2696165 | .6213926 |
| 2007 | .5455683 | .1382097 | 3.95 | 0.000 | .2728588 | .8182777 |
| 2008 | .2929549 | .1245018 | 2.35 | 0.020 | .0472934 | .5386164 |
| 2009 | .1452358 | .160378 | 0.91 | 0.366 | -.1712152 | .4616869 |
| 2010 | .4197369 | .0976442 | 4.30 | 0.000 | .2270695 | .6124042 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2011 | .7315608 | .1189096 | 6.15 | 0.000 | .4969334 | .9661881 |
| 2012 | .5461511 | .1259123 | 4.34 | 0.000 | .2977064 | .7945957 |
| 2013 | .5730976 | .1250406 | 4.58 | 0.000 | .3263729 | .8198224 |
| 2014 | .7763745 | .1284286 | 6.05 | 0.000 | .5229648 | 1.029784 |
| 2015 | .5117827 | .1240118 | 4.13 | 0.000 | .2670881 | .7564774 |
| 2016 | .5119249 | .1203708 | 4.25 | 0.000 | .2744144 | .7494355 |
| 2017 | .605396 | .1523733 | 3.97 | 0.000 | .3047395 | .9060525 |
| 2018 | .5341329 | .0952462 | 5.61 | 0.000 | .3461973 | .7220685 |
| 2019 | .7062273 | .1225156 | 5.76 | 0.000 | .4644848 | .9479698 |
| 2020 | .5709695 | .1179416 | 4.84 | 0.000 | .3382521 | .8036868 |
| 2021 | .544902 | .241702 | 2.25 | 0.025 | .0679859 | 1.021818 |
| 2022 | .8470864 | .1531584 | 5.53 | 0.000 | .5448808 | 1.149292 |
| | | | | | | |
| _cons | 15.65834 | .7775387 | 20.14 | 0.000 | 14.12413 | 17.19255 |

| | | **Robust** | | | | |
|---|---|---|---|---|---|---|
| **log_ebit_w** | **Coefficient** | **std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
| log_total_penalty_vtype_w | .1479312 | .0993446 | 1.49 | 0.138 | -.0480913 | .3439538 |
| log_revt_w | .4111751 | .3627873 | 1.13 | 0.259 | -.3046611 | 1.127011 |
| sqrt_debt_at_w | -1.661447 | 2.615591 | -0.64 | 0.526 | -6.822418 | 3.499525 |
| sqrt_gpm_w | -.4964719 | 2.974841 | -0.17 | 0.868 | -6.366301 | 5.373357 |
| sqrt_npm_w | -4.033307 | 5.990882 | -0.67 | 0.502 | -15.85426 | 7.787643 |
| sqrt_roa_w | -2.575602 | 2.756692 | -0.93 | 0.351 | -8.014988 | 2.863785 |
| sqrt_roe_w | 7.071912 | 4.657807 | 1.52 | 0.131 | -2.118673 | 16.2625 |
| | | | | | | |
| **year** | | | | | | |
| 2001 | -.1832276 | .6742146 | -0.27 | 0.786 | -1.513559 | 1.147104 |
| 2002 | .1656177 | .5223283 | 0.32 | 0.752 | -.865018 | 1.196253 |
| 2003 | -.1268913 | .4198302 | -0.30 | 0.763 | -.9552822 | .7014995 |
| 2004 | -.1035063 | .4692331 | -0.22 | 0.826 | -1.029377 | .8223642 |
| 2005 | -.278435 | .7064771 | -0.39 | 0.694 | -1.672425 | 1.115555 |
| 2006 | -1.235318 | 1.120892 | -1.10 | 0.272 | -3.447014 | .9763783 |
| 2007 | -.0923015 | .7868044 | -0.12 | 0.907 | -1.64479 | 1.460187 |
| 2008 | -.7890183 | .8168609 | -0.97 | 0.335 | -2.400813 | .8227765 |
| 2009 | -.2238871 | .6970805 | -0.32 | 0.748 | -1.599336 | 1.151562 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2010 | -.5474116 | .7544387 | -0.73 | 0.469 | -2.036038 | .9412144 |
| 2011 | -.6791512 | .7605544 | -0.89 | 0.373 | -2.179844 | .821542 |
| 2012 | -.5846065 | 1.093644 | -0.53 | 0.594 | -2.742539 | 1.573325 |
| 2013 | -.4331365 | 1.025663 | -0.42 | 0.673 | -2.45693 | 1.590657 |
| 2014 | -.4336613 | .858365 | -0.51 | 0.614 | -2.12735 | 1.260028 |
| 2015 | -.4121057 | .8292547 | -0.50 | 0.620 | -2.048355 | 1.224144 |
| 2016 | .8130158 | .8358021 | 0.97 | 0.332 | -.8361529 | 2.462185 |
| 2017 | -.0311748 | 1.127415 | -0.03 | 0.978 | -2.255741 | 2.193391 |
| 2018 | .9835438 | 2.114401 | 0.47 | 0.642 | -3.188502 | 5.155589 |
| 2019 | -1.080218 | 1.517124 | -0.71 | 0.477 | -4.073742 | 1.913306 |
| 2020 | -.9667024 | 1.795829 | -0.54 | 0.591 | -4.510155 | 2.57675 |
| 2021 | -.5876494 | 1.166851 | -0.50 | 0.615 | -2.89003 | 1.714732 |
| 2022 | -.8318846 | 1.056056 | -0.79 | 0.432 | -2.915649 | 1.25188 |
| | | | | | | |
| _cons | 9.497934 | 7.382709 | 1.29 | 0.200 | -5.06931 | 24.06518 |

**Appendix N: Fixed Effect Panel Regression Output (Pipeline Safety Violations)**

| | | **Robust** | | | | |
|---|---|---|---|---|---|---|
| **log_revt_w** | **Coefficient** | **std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
| log_total_penalty_vtype_w | .0161306 | .0284267 | 0.57 | 0.574 | -.0415214 | .0737826 |
| log_ebit_w | .2100177 | .1043735 | 2.01 | 0.052 | -.0016615 | .421697 |
| sqrt_debt_at_w | -.3928911 | .8833529 | -0.44 | 0.659 | -2.184414 | 1.398632 |
| sqrt_gpm_w | -.354676 | 1.133836 | -0.31 | 0.756 | -2.654202 | 1.94485 |
| sqrt_npm_w | -7.954347 | 3.271285 | -2.43 | 0.020 | -14.58882 | -1.319873 |
| sqrt_roa_w | 1.960729 | 1.103576 | 1.78 | 0.084 | -.2774269 | 4.198885 |
| sqrt_roe_w | 2.298333 | 1.913957 | 1.20 | 0.238 | -1.583353 | 6.180018 |
| | | | | | | |
| **year** | | | | | | |
| 2003 | .0925265 | .1754688 | 0.53 | 0.601 | -.2633408 | .4483938 |
| 2004 | .21961 | .1180368 | 1.86 | 0.071 | -.0197797 | .4589998 |
| 2005 | .4599746 | .1266853 | 3.63 | 0.001 | .2030448 | .7169044 |
| 2006 | .4557936 | .145155 | 3.14 | 0.003 | .1614055 | .7501817 |
| 2007 | .656857 | .1415744 | 4.64 | 0.000 | .3697307 | .9439833 |
| 2008 | .6727438 | .1844489 | 3.65 | 0.001 | .2986641 | 1.046824 |
| 2009 | .3564225 | .1112417 | 3.20 | 0.003 | .1308139 | .5820311 |
| 2010 | .6144041 | .1302429 | 4.72 | 0.000 | .3502592 | .8785489 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2011 | .5668127 | .1662369 | 3.41 | 0.002 | .2296686 | .9039568 |
| 2012 | .4249401 | .1409394 | 3.02 | 0.005 | .1391016 | .7107785 |
| 2013 | .9075096 | .2092901 | 4.34 | 0.000 | .4830497 | 1.33197 |
| 2014 | .8006307 | .1720434 | 4.65 | 0.000 | .4517106 | 1.149551 |
| 2015 | .5257975 | .1218553 | 4.31 | 0.000 | .2786636 | .7729314 |
| 2016 | .5781651 | .0985959 | 5.86 | 0.000 | .3782034 | .7781268 |
| 2017 | .3761214 | .1616369 | 2.33 | 0.026 | .0483064 | .7039363 |
| 2018 | 1.029047 | .2236321 | 4.60 | 0.000 | .5754999 | 1.482594 |
| 2019 | 1.099937 | .25758 | 4.27 | 0.000 | .5775406 | 1.622333 |
| 2020 | .8107221 | .2468533 | 3.28 | 0.002 | .3100803 | 1.311364 |
| 2021 | .6768674 | .1611519 | 4.20 | 0.000 | .3500361 | 1.003699 |
| 2022 | 1.137085 | .2712598 | 4.19 | 0.000 | .5869448 | 1.687225 |
| | | | | | | |
| _cons | 16.56434 | 2.184724 | 7.58 | 0.000 | 12.13352 | 20.99517 |

| | | **Robust** | | | | |
|---|---|---|---|---|---|---|
| **log_ebit_w** | **Coefficient** | **std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
| log_total_penalty_vtype_w | -.1021023 | .0463395 | -2.20 | 0.034 | -.1960831 | -.0081215 |
| log_revt_w | .2594875 | .0912748 | 2.84 | 0.007 | .0743736 | .4446013 |
| sqrt_debt_at_w | -1.497792 | .7004216 | -2.14 | 0.039 | -2.918313 | -.077271 |
| sqrt_gpm_w | 1.774249 | .6645493 | 2.67 | 0.011 | .426481 | 3.122018 |
| sqrt_npm_w | -3.489963 | 1.985926 | -1.76 | 0.087 | -7.517607 | .5376802 |
| sqrt_roa_w | -.6073668 | 1.329203 | -0.46 | 0.650 | -3.303115 | 2.088382 |
| sqrt_roe_w | 6.425183 | 2.643308 | 2.43 | 0.020 | 1.064307 | 11.78606 |
| | | | | | | |
| **year** | | | | | | |
| 2003 | .2868229 | .1537483 | 1.87 | 0.070 | -.0249931 | .598639 |
| 2004 | .2002138 | .1452607 | 1.38 | 0.177 | -.0943885 | .4948161 |
| 2005 | .2393923 | .145262 | 1.65 | 0.108 | -.0552127 | .5339972 |
| 2006 | .1016395 | .1612284 | 0.63 | 0.532 | -.2253468 | .4286259 |
| 2007 | .2619944 | .170189 | 1.54 | 0.132 | -.0831648 | .6071537 |
| 2008 | .4055751 | .1253692 | 3.24 | 0.003 | .1513145 | .6598357 |
| 2009 | .170825 | .1772202 | 0.96 | 0.342 | -.1885942 | .5302443 |
| 2010 | .4668058 | .1051578 | 4.44 | 0.000 | .253536 | .6800756 |
| 2011 | .472594 | .1721212 | 2.75 | 0.009 | .1235161 | .8216719 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2012 | .3197425 | .1385951 | 2.31 | 0.027 | .0386585 | .6008264 |
| 2013 | .5130874 | .2356597 | 2.18 | 0.036 | .0351474 | .9910274 |
| 2014 | .3563533 | .1631726 | 2.18 | 0.036 | .025424 | .6872826 |
| 2015 | .2338138 | .1216443 | 1.92 | 0.063 | -.0128922 | .4805199 |
| 2016 | .0863478 | .1757343 | 0.49 | 0.626 | -.2700578 | .4427534 |
| 2017 | .0453293 | .1779699 | 0.25 | 0.800 | -.3156104 | .406269 |
| 2018 | .4143637 | .2187472 | 1.89 | 0.066 | -.0292762 | .8580037 |
| 2019 | .1334231 | .273181 | 0.49 | 0.628 | -.4206137 | .6874599 |
| 2020 | -.033643 | .5127749 | -0.07 | 0.948 | -1.073599 | 1.006313 |
| 2021 | .572998 | .2932517 | 1.95 | 0.059 | -.0217439 | 1.16774 |
| 2022 | .7960628 | .3469281 | 2.29 | 0.028 | .09246 | 1.499666 |
| | | | | | | |
| _cons | 6.53551 | 2.008216 | 3.25 | 0.002 | 2.46266 | 10.60836 |

**Appendix O: Fixed Effect Panel Regression Output (Oil and Gas Drilling Violations)**

| **log_revt_w** | **Coefficient** | **Robust std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
|---|---|---|---|---|---|---|
| log_total_penalty_vtype_w | .0149166 | .0364889 | 0.41 | 0.686 | -.0602337 | .090067 |
| log_ebit_w | .0064654 | .0045125 | 1.43 | 0.164 | -.0028283 | .0157591 |
| sqrt_debt_at_w | -.7227443 | .4035716 | -1.79 | 0.085 | -1.553916 | .1084269 |
| sqrt_gpm_w | -1.439278 | .6767834 | -2.13 | 0.043 | -2.83314 | -.0454168 |
| sqrt_npm_w | -.184125 | .4018925 | -0.46 | 0.651 | -1.011838 | .643588 |
| sqrt_roa_w | 1.900745 | .7694034 | 2.47 | 0.021 | .3161292 | 3.485361 |
| sqrt_roe_w | .4517735 | .3118341 | 1.45 | 0.160 | -.1904609 | 1.094008 |
| | | | | | | |
| **year** | | | | | | |
| 2001 | -.8693721 | .2896807 | -3.00 | 0.006 | -1.465981 | -.2727634 |
| 2002 | -.0158116 | .1982046 | -0.08 | 0.937 | -.4240217 | .3923985 |
| 2003 | .3364148 | .1810846 | 1.86 | 0.075 | -.0365359 | .7093656 |
| 2004 | .4258301 | .1853153 | 2.30 | 0.030 | .044166 | .8074941 |
| 2005 | .4498291 | .1953659 | 2.30 | 0.030 | .0474655 | .8521926 |
| 2006 | .4500695 | .189 | 2.38 | 0.025 | .0608167 | .8393222 |
| 2007 | .7118285 | .2199587 | 3.24 | 0.003 | .2588151 | 1.164842 |
| 2008 | .8905786 | .2298533 | 3.87 | 0.001 | .417187 | 1.36397 |
| 2009 | .5984398 | .2848885 | 2.10 | 0.046 | .0117009 | 1.185179 |
| 2010 | .674908 | .1852485 | 3.64 | 0.001 | .2933816 | 1.056434 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2011 | .9471648 | .2747842 | 3.45 | 0.002 | .3812361 | 1.513094 |
| 2012 | .8678297 | .2653617 | 3.27 | 0.003 | .3213071 | 1.414352 |
| 2013 | 1.060318 | .2328296 | 4.55 | 0.000 | .5807966 | 1.53984 |
| 2014 | 1.061887 | .2503615 | 4.24 | 0.000 | .5462577 | 1.577516 |
| 2015 | .4799512 | .2223595 | 2.16 | 0.041 | .0219932 | .9379092 |
| 2016 | .6182401 | .3022671 | 2.05 | 0.051 | -.0042907 | 1.240771 |
| 2017 | .8231793 | .2463599 | 3.34 | 0.003 | .3157916 | 1.330567 |
| 2018 | .9033245 | .219524 | 4.11 | 0.000 | .4512064 | 1.355443 |
| 2020 | .6677407 | .3514732 | 1.90 | 0.069 | -.0561318 | 1.391613 |
| 2021 | .905686 | .2574007 | 3.52 | 0.002 | .3755593 | 1.435813 |
| 2022 | .7820924 | .2561696 | 3.05 | 0.005 | .2545012 | 1.309684 |
| | | | | | | |
| _cons | 15.60012 | .5915981 | 26.37 | 0.000 | 14.3817 | 16.81854 |

| log_ebit_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_vtype_w | -.1141211 | .4327822 | -0.26 | 0.794 | -1.005453 | .7772105 |
| log_revt_w | 1.938061 | 1.661806 | 1.17 | 0.255 | -1.484493 | 5.360615 |
| sqrt_debt_at_w | 4.09481 | 4.704784 | 0.87 | 0.392 | -5.594875 | 13.78449 |
| sqrt_gpm_w | -.7502672 | 9.316538 | -0.08 | 0.936 | -19.93804 | 18.4375 |
| sqrt_npm_w | -12.54828 | 8.724195 | -1.44 | 0.163 | -30.51609 | 5.419539 |
| sqrt_roa_w | 11.89706 | 6.943083 | 1.71 | 0.099 | -2.402491 | 26.1966 |
| sqrt_roe_w | -.3509156 | 7.335417 | -0.05 | 0.962 | -15.45849 | 14.75666 |
| | | | | | | |
| **year** | | | | | | |
| 2001 | 2.385092 | 2.475751 | 0.96 | 0.345 | -2.713814 | 7.483997 |
| 2002 | .6265961 | .8491666 | 0.74 | 0.467 | -1.122295 | 2.375487 |
| 2003 | .6981486 | 1.611654 | 0.43 | 0.669 | -2.621115 | 4.017412 |
| 2004 | .8450921 | 1.354805 | 0.62 | 0.538 | -1.94518 | 3.635364 |
| 2005 | .5454728 | 1.249086 | 0.44 | 0.666 | -2.027068 | 3.118014 |
| 2006 | -.0761269 | 1.770203 | -0.04 | 0.966 | -3.721928 | 3.569675 |
| 2007 | .5545662 | 1.986179 | 0.28 | 0.782 | -3.536045 | 4.645177 |
| 2008 | -4.663 | 5.151495 | -0.91 | 0.374 | -15.2727 | 5.946703 |
| 2009 | -2.295807 | 2.94898 | -0.78 | 0.444 | -8.369345 | 3.777731 |
| 2010 | -.2865818 | 1.728638 | -0.17 | 0.870 | -3.846778 | 3.273615 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2011 | -1.869064 | 3.12374 | -0.60 | 0.555 | -8.302528 | 4.564399 |
| 2012 | .7320069 | 2.242631 | 0.33 | 0.747 | -3.886778 | 5.350791 |
| 2013 | .5464063 | 2.167475 | 0.25 | 0.803 | -3.917593 | 5.010405 |
| 2014 | .5133219 | 1.954378 | 0.26 | 0.795 | -3.511794 | 4.538438 |
| 2015 | -11.61008 | 6.800778 | -1.71 | 0.100 | -25.61655 | 2.396385 |
| 2016 | -8.837076 | 6.661329 | -1.33 | 0.197 | -22.55634 | 4.882188 |
| 2017 | -1.891555 | 2.875539 | -0.66 | 0.517 | -7.813838 | 4.030729 |
| 2018 | 2.636514 | 2.251202 | 1.17 | 0.253 | -1.999922 | 7.272951 |
| 2020 | -14.04775 | 5.702197 | -2.46 | 0.021 | -25.79164 | -2.303854 |
| 2021 | -2.219357 | 2.884818 | -0.77 | 0.449 | -8.16075 | 3.722037 |
| 2022 | 2.603045 | 2.529746 | 1.03 | 0.313 | -2.607065 | 7.813155 |
| _cons | -14.30157 | 29.5119 | -0.48 | 0.632 | -75.08246 | 46.47933 |

## Appendix P: Event Study Regression Output (Across all Chosen Violations)

Regression for Air Pollution

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_vtype_w | .0001245 | .0001377 | 0.90 | 0.366 | -.0001457 | .0003946 |
| log_revt_w | .0001488 | .0001927 | 0.77 | 0.440 | -.0002291 | .0005267 |
| log_ebit_w | .0000169 | .0001664 | 0.10 | 0.919 | -.0003093 | .0003432 |
| sqrt_de_ratio_w | .000424 | .0009517 | 0.45 | 0.656 | -.0014426 | .0022905 |
| sqrt_gpm_w | .0016549 | .0019713 | 0.84 | 0.401 | -.0022115 | .0055213 |
| sqrt_npm_w | .0006836 | .0048932 | 0.14 | 0.889 | -.0089137 | .0102809 |
| sqrt_roa_w | .0003464 | .005236 | 0.07 | 0.947 | -.0099232 | .010616 |
| sqrt_roe_w | -.0005803 | .0047536 | -0.12 | 0.903 | -.0099037 | .0087432 |
| _cons | -.0038422 | .005512 | -0.70 | 0.486 | -.0146531 | .0069687 |

Regression for Water Pollution Violation

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_vtype_w | .0003421 | .0002633 | 1.30 | 0.195 | -.000176 | .0008602 |
| log_revt_w | .0009651 | .0004307 | 2.24 | 0.026 | .0001176 | .0018126 |
| log_ebit_w | -.0013247 | .0003776 | -3.51 | 0.001 | -.0020678 | -.0005816 |
| sqrt_de_ratio_w | -.0013737 | .0022285 | -0.62 | 0.538 | -.0057591 | .0030117 |
| sqrt_gpm_w | -.0015852 | .0053293 | -0.30 | 0.766 | -.0120724 | .008902 |

| | | | | | | |
|---|---|---|---|---|---|---|
| sqrt_npm_w | .0275022 | .0109978 | 2.50 | 0.013 | .0058602 | .0491442 |
| sqrt_roa_w | .0028497 | .0079431 | 0.36 | 0.720 | -.0127812 | .0184806 |
| sqrt_roe_w | -.0171897 | .0061999 | -2.77 | 0.006 | -.0293902 | -.0049893 |
| _cons | .0080489 | .0101154 | 0.80 | 0.427 | -.0118567 | .0279546 |

Regression for Hazardous Waste Violation

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_vtype_w | .0000677 | .0002181 | 0.31 | 0.757 | -.0003613 | .0004966 |
| log_revt_w | -.0001229 | .0003178 | -0.39 | 0.699 | -.0007479 | .0005021 |
| log_ebit_w | .0001733 | .0001563 | 1.11 | 0.268 | -.0001341 | .0004807 |
| sqrt_de_ratio_w | .0005877 | .0010263 | 0.57 | 0.567 | -.0014309 | .0026062 |
| sqrt_gpm_w | -.0022158 | .0050788 | -0.44 | 0.663 | -.0122045 | .007773 |
| sqrt_npm_w | -.0070483 | .0227878 | -0.31 | 0.757 | -.0518665 | .0377699 |
| sqrt_roa_w | .0094668 | .0095592 | 0.99 | 0.323 | -.0093339 | .0282675 |
| sqrt_roe_w | -.004881 | .0072375 | -0.67 | 0.501 | -.0191154 | .0093534 |
| _cons | .004401 | .0148362 | 0.30 | 0.767 | -.0247782 | .0335803 |

Regression for Pipeline Safety Violation

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_vtype_w | -.0007958 | .0005978 | -1.33 | 0.185 | -.0019773 | .0003856 |
| log_revt_w | .0003478 | .000655 | 0.53 | 0.596 | -.0009466 | .0016422 |
| log_ebit_w | -.0033971 | .001659 | -2.05 | 0.042 | -.0066756 | -.0001187 |
| sqrt_de_ratio_w | .0006326 | .0012993 | 0.49 | 0.627 | -.001935 | .0032002 |
| sqrt_gpm_w | .0041268 | .0058622 | 0.70 | 0.483 | -.0074576 | .0157112 |
| sqrt_npm_w | -.0262575 | .0173845 | -1.51 | 0.133 | -.0606113 | .0080963 |
| sqrt_roa_w | -.0115896 | .0094517 | -1.23 | 0.222 | -.0302673 | .0070882 |
| sqrt_roe_w | .0478121 | .0246502 | 1.94 | 0.054 | -.0008997 | .0965239 |
| _cons | .01196 | .0191292 | 0.63 | 0.533 | -.0258417 | .0497616 |

Regression for Oil and Gas Drilling Violation

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_vtype_w | .0004007 | .0007165 | 0.56 | 0.577 | -.0010144 | .0018159 |

| | | | | | | |
|---|---|---|---|---|---|---|
| log_revt_w | .0003488 | .0010864 | 0.32 | 0.749 | -.0017969 | .0024945 |
| log_ebit_w | .000146 | .0002298 | 0.64 | 0.526 | -.0003077 | .0005998 |
| sqrt_de_ratio_w | -.0026149 | .0055711 | -0.47 | 0.639 | -.0136178 | .0083879 |
| sqrt_gpm_w | .0021757 | .0080108 | 0.27 | 0.786 | -.0136455 | .017997 |
| sqrt_npm_w | -.0233293 | .0164132 | -1.42 | 0.157 | -.0557454 | .0090868 |
| sqrt_roa_w | .0122364 | .0224134 | 0.55 | 0.586 | -.0320299 | .0565027 |
| sqrt_roe_w | .0161345 | .0203151 | 0.79 | 0.428 | -.0239877 | .0562566 |
| _cons | .0022881 | .0253369 | 0.09 | 0.928 | -.0477522 | .0523284 |

**Appendix Q: Penalty Amounts across Industries (winsorized)**

| **industry_group** | **N** | **Min** | **Max** |
|---|---|---|---|
| Manufacturing | 2,135 | 5 | 117,153.8 |
| Mining, Quarrying, and Oil and Gas Extraction | 558 | 5 | 117,153.8 |
| Transportation and Warehousing | 278 | 5 | 117,153.8 |

**Appendix R: Fixed Effect Panel Regression Output (Manufacturing)**

| | | **Robust** | | | | |
|---|---|---|---|---|---|---|
| **log_revt_w** | **Coefficient** | **std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
| log_total_penalty_yearly_w | -.0388605 | .0075277 | -5.16 | 0.000 | -.0536654 | -.0240557 |
| log_ebit_w | .0310195 | .0108139 | 2.87 | 0.004 | .0097518 | .0522872 |
| sqrt_debt_at_w | .6207086 | .2762087 | 2.25 | 0.025 | .0774871 | 1.16393 |
| sqrt_gpm_w | -.0666609 | .772046 | -0.09 | 0.931 | -1.585049 | 1.451727 |
| sqrt_npm_w | 1.596424 | .4963866 | 3.22 | 0.001 | .6201774 | 2.572671 |
| sqrt_roa_w | -.0480167 | .6312267 | -0.08 | 0.939 | -1.289455 | 1.193421 |
| sqrt_roe_w | .2130251 | .1300067 | 1.64 | 0.102 | -.0426601 | .4687102 |
| _cons | 13.03667 | .5006389 | 26.04 | 0.000 | 12.05206 | 14.02128 |

| | | **Robust** | | | | |
|---|---|---|---|---|---|---|
| **log_ebit_w** | **Coefficient** | **std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
| log_total_penalty_yearly_w | .0756699 | .0491923 | 1.54 | 0.125 | -.021077 | .1724168 |
| log_revt_w | .4064897 | .1585888 | 2.56 | 0.011 | .0945919 | .7183875 |
| sqrt_debt_at_w | -.2264778 | .3610523 | -0.63 | 0.531 | -.9365618 | .4836063 |
| sqrt_gpm_w | -1.447055 | 1.626265 | -0.89 | 0.374 | -4.645441 | 1.751331 |

| | | | | | | |
|---|---|---|---|---|---|---|
| sqrt_npm_w | -1.31735 | .9243452 | -1.43 | 0.155 | -3.135266 | .500566 |
| sqrt_roa_w | 2.529496 | 2.58028 | 0.98 | 0.328 | -2.545159 | 7.604152 |
| sqrt_roe_w | 2.026614 | 1.496044 | 1.35 | 0.176 | -.9156661 | 4.968893 |
| _cons | 8.596183 | 1.952849 | 4.40 | 0.000 | 4.7555 | 12.43687 |

**Appendix S: Fixed Effect Panel Regression Output (Mining, Quarrying, and Oil and Gas Extraction)**

| **log_revt_w** | **Coefficient** | **Robust std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | .0034135 | .0147588 | 0.23 | 0.818 | -.0260076 | .0328346 |
| log_ebit_w | .0154165 | .0073741 | 2.09 | 0.040 | .0007164 | .0301166 |
| sqrt_debt_at_w | -1.026265 | .6134099 | -1.67 | 0.099 | -2.249076 | .196545 |
| sqrt_gpm_w | -1.583513 | .5581414 | -2.84 | 0.006 | -2.696148 | -.4708783 |
| sqrt_npm_w | -.3322549 | .2833643 | -1.17 | 0.245 | -.8971314 | .2326216 |
| sqrt_roa_w | 2.38747 | .7338827 | 3.25 | 0.002 | .9245013 | 3.850438 |
| sqrt_roe_w | .4716734 | .3535159 | 1.33 | 0.186 | -.2330476 | 1.176394 |
| _cons | 15.22248 | .6246376 | 24.37 | 0.000 | 13.97728 | 16.46767 |

| **log_ebit_w** | **Coefficient** | **Robust std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | .0717754 | .151388 | 0.47 | 0.637 | -.230011 | .3735618 |
| log_revt_w | .8879703 | .4061319 | 2.19 | 0.032 | .0783611 | 1.697579 |
| sqrt_debt_at_w | 4.147265 | 3.249049 | 1.28 | 0.206 | -2.329596 | 10.62413 |
| sqrt_gpm_w | 2.054644 | 2.919563 | 0.70 | 0.484 | -3.765399 | 7.874688 |
| sqrt_npm_w | 3.857988 | 3.093311 | 1.25 | 0.216 | -2.308414 | 10.02439 |
| sqrt_roa_w | 6.857715 | 4.636889 | 1.48 | 0.144 | -2.385755 | 16.10119 |
| sqrt_roe_w | -3.5738 | 3.751687 | -0.95 | 0.344 | -11.05265 | 3.905052 |
| _cons | -4.05712 | 7.025521 | -0.58 | 0.565 | -18.06224 | 9.948001 |

**Appendix T: Fixed Effect Panel Regression Output (Transportation and Warehousing)**

| **log_revt_w** | **Coefficient** | **Robust std. err.** | **t** | **P>\|t\|** | **[95% conf. interval]** | |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | -.006368 | .0118849 | -0.54 | 0.596 | -.0305767 | .0178407 |
| log_ebit_w | .0538544 | .0200482 | 2.69 | 0.011 | .0130176 | .0946913 |
| sqrt_debt_at_w | 1.303384 | .8215322 | 1.59 | 0.122 | -.3700227 | 2.97679 |
| sqrt_gpm_w | .7636407 | 1.073963 | 0.71 | 0.482 | -1.423951 | 2.951233 |
| sqrt_npm_w | -4.294792 | 2.826768 | -1.52 | 0.138 | -10.05273 | 1.463146 |
| sqrt_roa_w | 3.867914 | 2.464391 | 1.57 | 0.126 | -1.151887 | 8.887715 |
| sqrt_roe_w | .5524996 | .4487632 | 1.23 | 0.227 | -.3616011 | 1.4666 |
| _cons | 15.24237 | .9600082 | 15.88 | 0.000 | 13.28689 | 17.19784 |

| log_ebit_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | .0444767 | .0454688 | 0.98 | 0.335 | -.0481401 | .1370935 |
| log_revt_w | .8910292 | .5975112 | 1.49 | 0.146 | -.3260612 | 2.10812 |
| sqrt_debt_at_w | -1.622618 | 1.745881 | -0.93 | 0.360 | -5.178861 | 1.933625 |
| sqrt_gpm_w | .0278393 | 1.747799 | 0.02 | 0.987 | -3.532312 | 3.58799 |
| sqrt_npm_w | 7.501579 | 7.064081 | 1.06 | 0.296 | -6.887483 | 21.89064 |
| sqrt_roa_w | .7587307 | .9779299 | 0.78 | 0.444 | -1.233247 | 2.750709 |
| sqrt_roe_w | -.3470452 | 1.093907 | -0.32 | 0.753 | -2.57526 | 1.88117 |
| _cons | -3.37614 | 11.85249 | -0.28 | 0.778 | -27.51887 | 20.76659 |

## Appendix U: Event Study Regression Output (Across all Chosen Industries)

Regression for Industry: Manufacturing

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | .0000294 | .0001007 | 0.29 | 0.770 | -.000168 | .0002268 |
| log_revt_w | -9.47e-06 | .0001351 | -0.07 | 0.944 | -.0002744 | .0002555 |
| log_ebit_w | .0000563 | .0001038 | 0.54 | 0.587 | -.0001472 | .0002599 |
| sqrt_de_ratio_w | .0002405 | .0004084 | 0.59 | 0.556 | -.0005602 | .0010412 |
| sqrt_gpm_w | .0022245 | .001545 | 1.44 | 0.150 | -.0008046 | .0052536 |
| sqrt_npm_w | -.0073259 | .0069017 | -1.06 | 0.289 | -.0208575 | .0062057 |
| sqrt_roa_w | .0020609 | .0033969 | 0.61 | 0.544 | -.0045991 | .0087208 |
| sqrt_roe_w | .0002097 | .0023745 | 0.09 | 0.930 | -.0044458 | .0048651 |
| _cons | .0020058 | .0051334 | 0.39 | 0.696 | -.0080589 | .0120705 |

Regression for Industry: Mining, Quarrying, and Oil and Gas Extraction

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | .0002269 | .0002587 | 0.88 | 0.381 | -.0002807 | .0007344 |
| log_revt_w | -.000152 | .0003831 | -0.40 | 0.692 | -.0009038 | .0005997 |
| log_ebit_w | -.0000226 | .0001472 | -0.15 | 0.878 | -.0003116 | .0002663 |
| sqrt_de_ratio_w | -.000048 | .0025974 | -0.02 | 0.985 | -.0051451 | .0050491 |
| sqrt_gpm_w | -.0028635 | .0030218 | -0.95 | 0.344 | -.0087933 | .0030663 |
| sqrt_npm_w | .0044194 | .004843 | 0.91 | 0.362 | -.0050844 | .0139232 |
| sqrt_roa_w | .0003383 | .0076913 | 0.04 | 0.965 | -.0147547 | .0154314 |
| sqrt_roe_w | -.0019414 | .0055198 | -0.35 | 0.725 | -.0127733 | .0088905 |
| _cons | .0055701 | .0099994 | 0.56 | 0.578 | -.0140524 | .0251927 |

Regression for Industry: Transportation and Warehousing

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | .0001632 | .0002491 | 0.66 | 0.513 | -.0003264 | .0006529 |
| log_revt_w | -.0006368 | .0007235 | -0.88 | 0.379 | -.0020587 | .000785 |
| log_ebit_w | .0016176 | .0000976 | 16.57 | 0.000 | .0014258 | .0018095 |
| sqrt_de_ratio_w | .0020377 | .0010392 | 1.96 | 0.051 | -4.66e-06 | .0040801 |
| sqrt_gpm_w | -.0062535 | .0057229 | -1.09 | 0.275 | -.0175006 | .0049935 |
| sqrt_npm_w | .0035592 | .0112047 | 0.32 | 0.751 | -.0184611 | .0255796 |
| sqrt_roa_w | .0032709 | .0139855 | 0.23 | 0.815 | -.0242145 | .0307563 |
| sqrt_roe_w | -.0116934 | .0104415 | -1.12 | 0.263 | -.0322138 | .0088269 |
| _cons | -.0100522 | .0130457 | -0.77 | 0.441 | -.0356905 | .0155861 |

## Appendix V: Company Sizes Across long-term Dataset

| size_group | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Large | 1,118 | 18,375,672 | 6,595,551.270 | 9,754,967 | 30,569,000 |
| Medium | 1,112 | 5,877,083 | 1,938,344.989 | 2,945,786 | 9,723,375 |
| Small | 1,117 | 1,456,477.7 | 803,987.287 | 123,662 | 2,934,010.3 |

| | | | | | |
|---|---|---|---|---|---|
| Very Large | 1,108 | 99,896,271 | 107,993,048.899 | 30,699,000 | 5.523e+08 |

**Appendix W: Penalty Amounts across Company Sizes**

| size_group | N | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Large | 1,118 | 533.5612 | 8727.143 | 5 | 263400 |
| Medium | 1,112 | 832.0178 | 9019.66 | .408 | 270000 |
| Small | 1,118 | 5059.755 | 57900.17 | 5 | 1028000 |
| Very Large | 1,108 | 7784.157 | 147565 | 5 | 4675000 |

**Appendix X: Fixed Effect Panel Regression Output (Small Companies)**

| log_revt_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | -.0536227 | .0164333 | -3.26 | 0.001 | -.0859737 | -.0212717 |
| log_ebit_w | 3.800582 | 1.711975 | 2.22 | 0.027 | .4303403 | 7.170824 |
| sqrt_debt_at_w | .2720236 | .2723812 | 1.00 | 0.319 | -.2641936 | .8082408 |
| sqrt_gpm_w | -.2037961 | .3826668 | -0.53 | 0.595 | -.9571247 | .5495325 |
| sqrt_npm_w | .8797044 | .5841549 | 1.51 | 0.133 | -.2702792 | 2.029688 |
| sqrt_roa_w | -.8207521 | .7695781 | -1.07 | 0.287 | -2.335765 | .6942607 |
| sqrt_roe_w | .2458276 | .2034805 | 1.21 | 0.228 | -.1547498 | .646405 |
| _cons | -44.37755 | 25.64897 | -1.73 | 0.085 | -94.87083 | 6.115731 |

| log_ebit_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | -.0003479 | .001367 | -0.25 | 0.799 | -.003039 | .0023432 |
| log_revt_w | .0354005 | .0052509 | 6.74 | 0.000 | .0250634 | .0457376 |
| sqrt_debt_at_w | .0036245 | .0264272 | 0.14 | 0.891 | -.0484008 | .0556498 |
| sqrt_gpm_w | .043868 | .0519713 | 0.84 | 0.399 | -.0584441 | .1461801 |
| sqrt_npm_w | -.0283069 | .1302074 | -0.22 | 0.828 | -.2846369 | .2280231 |
| sqrt_roa_w | .1070358 | .0442447 | 2.42 | 0.016 | .0199344 | .1941372 |
| sqrt_roe_w | .0063708 | .0145012 | 0.44 | 0.661 | -.0221767 | .0349183 |
| _cons | 14.50623 | .0849029 | 170.86 | 0.000 | 14.33909 | 14.67338 |

**Appendix Y: Fixed Effect Panel Regression Output (Medium Companies)**

| log_revt_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | -.033071 | .0115423 | -2.87 | 0.005 | -.0558385 | -.0103034 |
| log_ebit_w | .0190516 | .0134049 | 1.42 | 0.157 | -.00739 | .0454931 |
| sqrt_debt_at_w | 1.403198 | .3698258 | 3.79 | 0.000 | .6737062 | 2.13269 |
| sqrt_gpm_w | -.3371215 | .6340376 | -0.53 | 0.596 | -1.587779 | .9135357 |
| sqrt_npm_w | -.0001304 | .4235103 | -0.00 | 1.000 | -.8355164 | .8352556 |
| sqrt_roa_w | .9205933 | .9340785 | 0.99 | 0.326 | -.9219029 | 2.76309 |
| sqrt_roe_w | .4150581 | .1551071 | 2.68 | 0.008 | .1091049 | .7210113 |
| _cons | 13.12289 | .404175 | 32.47 | 0.000 | 12.32565 | 13.92014 |

| log_ebit_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | .0247566 | .0157953 | 1.57 | 0.119 | -.0064001 | .0559132 |
| log_revt_w | .1392495 | .0559857 | 2.49 | 0.014 | .0288161 | .249683 |
| sqrt_debt_at_w | -.5167918 | .4512097 | -1.15 | 0.254 | -1.406816 | .3732321 |
| sqrt_gpm_w | 4.256131 | 2.371051 | 1.80 | 0.074 | -.4208339 | 8.933096 |
| sqrt_npm_w | .1147828 | 2.19492 | 0.05 | 0.958 | -4.214759 | 4.444325 |
| sqrt_roa_w | .8876265 | 1.054064 | 0.84 | 0.401 | -1.191544 | 2.966797 |
| sqrt_roe_w | -.2907766 | 1.465874 | -0.20 | 0.843 | -3.182255 | 2.600701 |
| _cons | 11.05759 | 1.298229 | 8.52 | 0.000 | 8.496798 | 13.61838 |

**Appendix Z: Fixed Effect Panel Regression Output (Large Companies)**

| log_revt_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | -.0167624 | .0079759 | -2.10 | 0.038 | -.0325429 | -.000982 |
| log_ebit_w | .0265111 | .0207164 | 1.28 | 0.203 | -.0144769 | .0674991 |
| sqrt_debt_at_w | .1425842 | .3979063 | 0.36 | 0.721 | -.6446832 | .9298516 |
| sqrt_gpm_w | -1.692059 | .5573414 | -3.04 | 0.003 | -2.794772 | -.5893452 |
| sqrt_npm_w | .4980571 | .4665295 | 1.07 | 0.288 | -.4249829 | 1.421097 |
| sqrt_roa_w | 1.181974 | .5756623 | 2.05 | 0.042 | .0430123 | 2.320936 |
| sqrt_roe_w | .3041479 | .1558923 | 1.95 | 0.053 | -.0042888 | .6125846 |
| _cons | 15.26151 | .4233664 | 36.05 | 0.000 | 14.42387 | 16.09915 |

| log_ebit_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | .0477354 | .0289861 | 1.65 | 0.102 | -.0096143 | .1050852 |
| log_revt_w | .4057185 | .1896298 | 2.14 | 0.034 | .0305313 | .7809057 |
| sqrt_debt_at_w | 3.050769 | 1.796841 | 1.70 | 0.092 | -.5043242 | 6.605863 |
| sqrt_gpm_w | 2.156086 | 2.534814 | 0.85 | 0.397 | -2.859105 | 7.171277 |
| sqrt_npm_w | 6.856745 | 3.754456 | 1.83 | 0.070 | -.5715387 | 14.28503 |
| sqrt_roa_w | 1.494189 | 1.915721 | 0.78 | 0.437 | -2.296112 | 5.284491 |
| sqrt_roe_w | -1.392196 | 1.198147 | -1.16 | 0.247 | -3.762759 | .978367 |
| _cons | 1.817302 | 2.930183 | 0.62 | 0.536 | -3.980137 | 7.614742 |

## Appendix AA: Fixed Effect Panel Regression Output (Very Large Companies)

| log_revt_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | -.004336 | .0060338 | -0.72 | 0.474 | -.0163084 | .0076364 |
| log_ebit_w | .0221168 | .0072979 | 3.03 | 0.003 | .0076363 | .0365974 |
| sqrt_debt_at_w | .3976595 | .3913179 | 1.02 | 0.312 | -.3788 | 1.174119 |
| sqrt_gpm_w | -.1482276 | .5391684 | -0.27 | 0.784 | -1.218055 | .9215995 |
| sqrt_npm_w | -.3044297 | .5690203 | -0.54 | 0.594 | -1.433489 | .82463 |
| sqrt_roa_w | .2524212 | .8668186 | 0.29 | 0.772 | -1.467535 | 1.972377 |
| sqrt_roe_w | .5760856 | .2376975 | 2.42 | 0.017 | .1044422 | 1.047729 |
| _cons | 16.44033 | .3211542 | 51.19 | 0.000 | 15.80309 | 17.07757 |

| log_ebit_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_yearly_w | .0464145 | .0604721 | 0.77 | 0.445 | -.0735753 | .1664043 |
| log_revt_w | 1.130904 | .4211038 | 2.69 | 0.008 | .295343 | 1.966466 |
| sqrt_debt_at_w | -1.05174 | 1.054164 | -1.00 | 0.321 | -3.143431 | 1.03995 |
| sqrt_gpm_w | -.3083801 | 2.592558 | -0.12 | 0.906 | -5.452577 | 4.835817 |
| sqrt_npm_w | -1.935342 | 3.327433 | -0.58 | 0.562 | -8.537691 | 4.667006 |
| sqrt_roa_w | 8.866184 | 5.130827 | 1.73 | 0.087 | -1.314491 | 19.04686 |
| sqrt_roe_w | 4.39804 | 3.402401 | 1.29 | 0.199 | -2.353061 | 11.14914 |

| | | | | | | |
|---|---|---|---|---|---|---|
| _cons | -9.342844 | 7.379525 | -1.27 | 0.208 | -23.98542 | 5.299735 |

## Appendix AB: Event Study Regression Output (Across all Chosen Size Groups)

Regression for Small Companies

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | -.0000144 | .0002079 | -0.07 | 0.945 | -.0004221 | .0003933 |
| log_revt_w | -.000233 | .0003839 | -0.61 | 0.544 | -.000986 | .00052 |
| log_ebit_w | .0000337 | .0002119 | 0.16 | 0.874 | -.000382 | .0004494 |
| sqrt_de_ratio_w | -.0002062 | .000675 | -0.31 | 0.760 | -.00153 | .0011177 |
| sqrt_gpm_w | .0013304 | .0027091 | 0.49 | 0.623 | -.0039831 | .0066438 |
| sqrt_npm_w | -.0038088 | .0065958 | -0.58 | 0.564 | -.0167454 | .0091279 |
| sqrt_roa_w | .0047098 | .0054284 | 0.87 | 0.386 | -.0059372 | .0153568 |
| sqrt_roe_w | -.0044593 | .0029167 | -1.53 | 0.126 | -.01018 | .0012614 |
| _cons | .007826 | .0055338 | 1.41 | 0.157 | -.0030278 | .0186797 |

Regression for Medium Companies

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | -1.85e-06 | .0001592 | -0.01 | 0.991 | -.0003141 | .0003104 |
| log_revt_w | .0004198 | .0003805 | 1.10 | 0.270 | -.0003265 | .0011661 |
| log_ebit_w | -.0009321 | .0003187 | -2.92 | 0.003 | -.0015571 | -.000307 |
| sqrt_de_ratio_w | .0009229 | .000561 | 1.65 | 0.100 | -.0001774 | .0020233 |
| sqrt_gpm_w | -.0016419 | .0023736 | -0.69 | 0.489 | -.0062973 | .0030134 |
| sqrt_npm_w | .0039811 | .004897 | 0.81 | 0.416 | -.0056231 | .0135853 |
| sqrt_roa_w | .0005636 | .0052822 | 0.11 | 0.915 | -.0097962 | .0109233 |
| sqrt_roe_w | -.0021908 | .0029671 | -0.74 | 0.460 | -.00801 | .0036284 |
| _cons | .0034069 | .0068437 | 0.50 | 0.619 | -.0100153 | .0168292 |

Regression for Large Companies

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. | interval] |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | -.0000174 | .000123 | -0.14 | 0.888 | -.0002585 | .0002238 |
| log_revt_w | -.0000344 | .0004073 | -0.08 | 0.933 | -.0008333 | .0007645 |
| log_ebit_w | -4.28e-06 | .0002619 | -0.02 | 0.987 | -.000518 | .0005094 |

| | | | | | | |
|---|---|---|---|---|---|---|
| sqrt_de_ratio_w | -.0003687 | .000463 | -0.80 | 0.426 | -.0012767 | .0005394 |
| sqrt_gpm_w | .0000696 | .0020759 | 0.03 | 0.973 | -.0040021 | .0041412 |
| sqrt_npm_w | .0054832 | .0041977 | 1.31 | 0.192 | -.00275 | .0137163 |
| sqrt_roa_w | -.002481 | .0043649 | -0.57 | 0.570 | -.0110422 | .0060803 |
| sqrt_roe_w | .0035158 | .0032341 | 1.09 | 0.277 | -.0028274 | .0098591 |
| _cons | -.0052705 | .0068288 | -0.77 | 0.440 | -.0186643 | .0081233 |

Regression for Very Large Companies

| mean_aret_w | Coefficient | Robust std. err. | t | P>\|t\| | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| log_total_penalty_date_w | -6.90e-06 | .0000893 | -0.08 | 0.938 | -.0001821 | .0001683 |
| log_revt_w | -.0000465 | .0002105 | -0.22 | 0.825 | -.0004594 | .0003664 |
| log_ebit_w | .0000541 | .0000999 | 0.54 | 0.588 | -.0001418 | .0002499 |
| sqrt_de_ratio_w | -.0004684 | .0006358 | -0.74 | 0.461 | -.0017154 | .0007786 |
| sqrt_gpm_w | .0003715 | .0017169 | 0.22 | 0.829 | -.002996 | .003739 |
| sqrt_npm_w | .0038927 | .0047748 | 0.82 | 0.415 | -.0054722 | .0132576 |
| sqrt_roa_w | -.0009935 | .0038825 | -0.26 | 0.798 | -.0086083 | .0066214 |
| sqrt_roe_w | .0034859 | .0056954 | 0.61 | 0.541 | -.0076846 | .0146563 |
| _cons | -.004996 | .0059045 | -0.85 | 0.398 | -.0165766 | .0065846 |