

# Corporate Financial Misconduct Spillover Effect and Geographic Concentration

by

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## Abstract

This research investigates the relationship between industry geographic concentration and the spillover effect of corporate financial misconduct, with a focus on the financial and stock performance of peer firms located in the same industrial cluster as the company engaged in misconduct. The study generates industry clusters and industry centers using K-Means clustering. Using a sample of 772 corporate financial misconduct events, the study categorizes affected companies into peer companies and non-peer companies based on industrial clusters and time. T-Test and Difference-in-Difference regression analyses are conducted to compare the impact of the misconduct of peer and non-peer companies. The study finds that peer companies, located in the same industry center as the scandalous companies, experience a positive gain in financial performance compared to non-peer companies after the announcement of the misconduct. Moreover, if the scandalous firm was near the center of the industrial cluster, peer firms were more positively affected. The research contributes to the literature by involving both geographic identity and industrial identity, which raises a new possibility to study the spillover effect. Additionally, the study uses a large sample of misconduct data to investigate how geographic concentration affects the spillover effect. The findings have important implications for policymakers, investors, and corporate governance professionals seeking to understand and mitigate the negative consequences of corporate misconduct.

**KEY WORDS:** *Corporate Financial Misconduct, Intra-industry spillover effect, K-Means Clustering*

## Preface

The motivation for researching corporate financial misconduct spillover effect stems from the Enron Scandal in 2001 when the national economy was impacted. The spillover effect is a relatively new topic in the field of corporate financial misconduct. Researchers are still unaware of which kind of peer companies might be more vulnerable to corporate financial misconduct. Supported by the Business and Economics Honors Thesis Program, I am able to conduct empirical research about the consequences of corporate financial misconduct with the help of Professor Guodong Chen and Professor Chen Li. Throughout the statistical analysis of a large sample of data, I am able to reach some qualitative and quantitative opinions on the spillover effect and geographic factors.

# 1 Introduction

The share price of Enron Corporation (ENE) fell from \$90.75 to \$0.26 after its financial misconduct being revealed, implying a huge loss for the company. Corporate financial misconduct is a pervasive issue that can have far-reaching consequences beyond the firm itself. When the misconduct is revealed, a company will bear reputation cost which is 3.08 times of the inflation of market value by the misconduct (Karpoff et.al 2008). The household stock market will be negatively impacted due to corporate misconduct, holding for both scandalous firms and non-scandalous firms. (Giannetti and Wang 2014). Thus, corporate misconduct will undermine not only itself but related companies as well, which is the spillover effect. The spillover effect has been the subject of growing interest among scholars and policymakers. One factor that may exacerbate the spillover effect of corporate financial misconduct is geographic concentration. Fairhurst and Williams found that horizontal mergers based on geographic concentration are more like collisions (2017). Firms that share the same industry center as the company engaged in financial misconduct may be more likely to be affected by the misconduct, as it may lead to a loss of investor confidence and a decrease in economic activity in the surrounding area.

The goal of this research is to investigate the relationship between geographic concentration and the spillover effect of corporate misconduct. Specifically, the study hypothesizes that firms located in the same industry center as the company engaged in financial misconduct will experience a greater spillover effect compared with firms outside the industrial cluster. Also, the study hypothesizes that if the misconduct event is near the industrial center, the degree of spillover effect will be larger.

Based on a sample of 772 corporate financial misconduct events of listed companies in the US, the study divided the affected companies into two categories: peer

companies and non-peer companies. Peer companies were defined as those sharing the same industry center as the scandalous companies, while non-peer companies referred to other companies within the same industries. Industry centers were generated using the K-Means clustering method. By conducting a T-Test analysis and Difference-in-Difference panel regression analysis to compare the impact of the misconduct on the stock returns of peer and non-peer companies, I found peer companies would bear more shock in stock return compared with non-peer companies after the announcement of the misconduct.

The study finds that firms sharing the same industry center with scandalous firms are more likely to be affected positively by the spillover effect. Moreover, the positive effect is stronger if corporate misconduct happened near the industrial center. This highlights the importance of considering DTIC (distance-to-industry-center) when analyzing the impact of corporate financial misconduct, as it can significantly magnify the spillover effect.

The research contributes to the current literature in two aspects. Firstly, the paper sheds light on the interaction of geographic concentration and industry in the corporate financial misconduct spillover effect. Previous studies examine industrial similarity and geographic proximity respectively. But this study investigates the joint effect of both factors and raised a new dimension of study in spillover effect. Secondly, while some literature used case studies to investigate the spillover effect related to geographic factors, this study uses a large sample of corporate financial misconduct events to study the spillover effect. By analyzing a broad range of industries and firms, the study provides a more comprehensive understanding of the spillover effect. The use of a large sample of data also enhances the reliability of the findings.

The remainder of the paper is organized as follows. Section [2](#) summarizes the related literature in corporate financial misconduct. The KKML corporate financial

misconduct database, the historical data, and the main statistical methods are discussed in Section 3 and Section 4. Section 5 reports the results of both descriptive analysis and quantitative analysis, and Section 6 offers concluding remarks.

## 2 Literature

Cumming et al. (2015) identified four main areas of interest for researchers studying corporate financial misconduct: types of financial misconduct, causes of financial misconduct, consequences of financial misconduct, and regulations of financial misconduct. Cumming and Johan studied misconduct events from different countries and found distinct natures of reported events and distinct regulation methods, suggesting a stricter regulation. (2013). Becker explained the causes of financial misconduct by arguing that the benefits of misconduct outweighed the costs (1968). Financial misconduct may lead to stricter and more detailed regulations, which can help reduce corruption among companies (Zeume 2017).

Studying the consequences of corporate financial misconduct is a valuable and emerging topic. Earlier literature on corporate misconduct tended to focus on the impact of the misconduct within firms, such as the penalties of fines, jail sentences, and unemployment resulting from corporate financial misconduct (Karpoff et al. 2008).

More recently, researchers have focused more on the spillover effect of corporate misconduct. These studies have aimed to identify the characteristics that make some related firms more vulnerable to the effects of misconduct than others. Yu et al. studied the political connections between companies and the government in China and found that companies in the same industries were negatively affected when political connections influenced the magnitude of the negative spillover effect on share prices (2015). From the angle of corporate governance connection, director-interlocked firms

experience higher interest rates and stricter loan terms (Lai et al. 2019). Additionally, evidence was found that when firms have higher economic comparability, financial misconduct is less likely to happen because of the disciplines from rivalries (Boone et al. 2019).

This paper shares a similar research spirit with Barth et al. (2022). The authors used an event study to investigate the spillover effect of Volkswagen's Emission Scandal in 2015 by studying the stocks and bonds of competitor companies. Specifically, the authors studied whether geographic proximity affects the spillover effect by watching an event window  $[-2,2]$ . They finally found that geographic proximity contributes to the negative spillover effect because proximity serves as comparability.

This project differs from Barth et al. in two ways (2021). Firstly, instead of focusing on geographic proximity, this project focuses more on industry center and industry geographic clustering. That the spillover effect may be amplified by industry geographic concentration is supported by Fairhurst and Williams, who found that collisions are more likely in horizontal mergers based on geographic concentration (2017). Additionally, Wheeler claimed that the geographic concentration of industry is closely connected with the industry's productivity (2005). The industry concentration contributes to similarity and closer relationships among firms, which will influence the spillover effect. Secondly, instead of focusing on only one misconduct event, I used a larger sample of events and analyzed a larger sample of peer firms. In this way, this project examined the differential effect between "peer firms" (firms in the same FF12 industry and in the same industry cluster of the scandalous firm) and "non-peer firms" (firms in the same FF12 industry but in a different industry cluster of the scandalous firm). In the staggered difference-in-difference setting, non-peer firms count as the controlled group while peer firms count as the treated group.



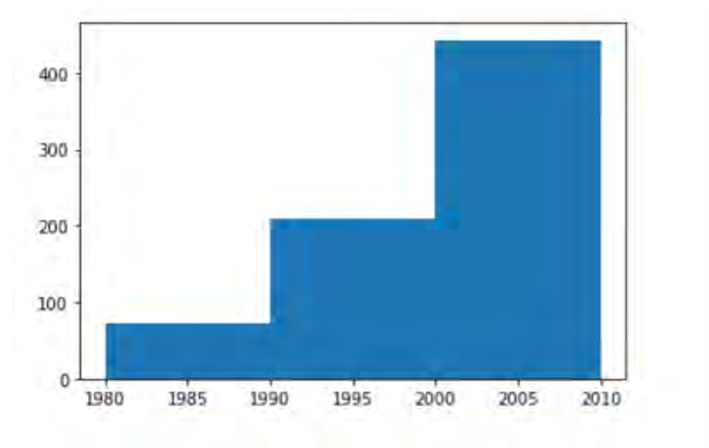


Figure 1: **Events Decade Distribution.** The figure shows the amount of events happening in each decade. The large number of events in decade 2000 may be led by SOX Act.

### 3 Data

The analysis sample is constructed by combining data from three databases: the KKLM Database (Karpoff et al. 2017), CompuStat, CRSP Monthly Stock, and SEC. Below, I explain how the analysis sample is constructed by combining the three databases.

#### 3.1 Main Data Sources

The corporate misconduct data comes from the KKLM Database collected and adjusted by Karpoff et al. (2017). This database contains 1310 corporate financial misconduct events from 1977 – 2012 from globally listed companies. In this project, only listed companies in the US were kept for further analysis. After deleting companies outside the US, there were 772 misconduct samples. The identification of each company is manually adjusted by checking SEC so that the misconduct events can be merged with CompuStat Database.

Figures fig. 1 and fig. 2 show the frequency of misconduct events in each decade

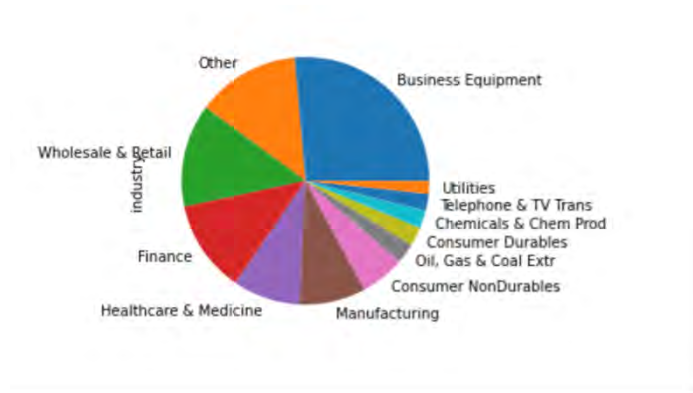


Figure 2: **Events Industry Distribution.** The figure shows the amount of events happening in each FF12 industry.

and industry. Less than 10 events happened before 1980 or after 2010. Thus, events before 1980 were merged into the decade of 1980 while events after 2010 were merged into the decade of 2000. From 2000 to 2010, there were more than 400 events, which was over half of the total number of events. This can be led by the Enron scandal in 2001 and SOX Act.

Fama and French 12 Industry Classification is used in this paper because this classification method is the most widely used method in current literature. There are relatively more misconduct events in industries of Business Equipment and Finance. Notably, new technology companies such as Amazon, Apple, and Uber are listed in the Business Equipment industry, which may contribute to the higher number of misconduct events due to a large number of companies in this industry.

### 3.2 Geographic Concentration Specification

To study the geographic factors, it is significant to measure the geographic features of the scandalous company and to identify peer companies that have geographic relationships with the scandalous company. For industry, the location of the industrial center and distances between companies are two factors that are measurable. Thus,

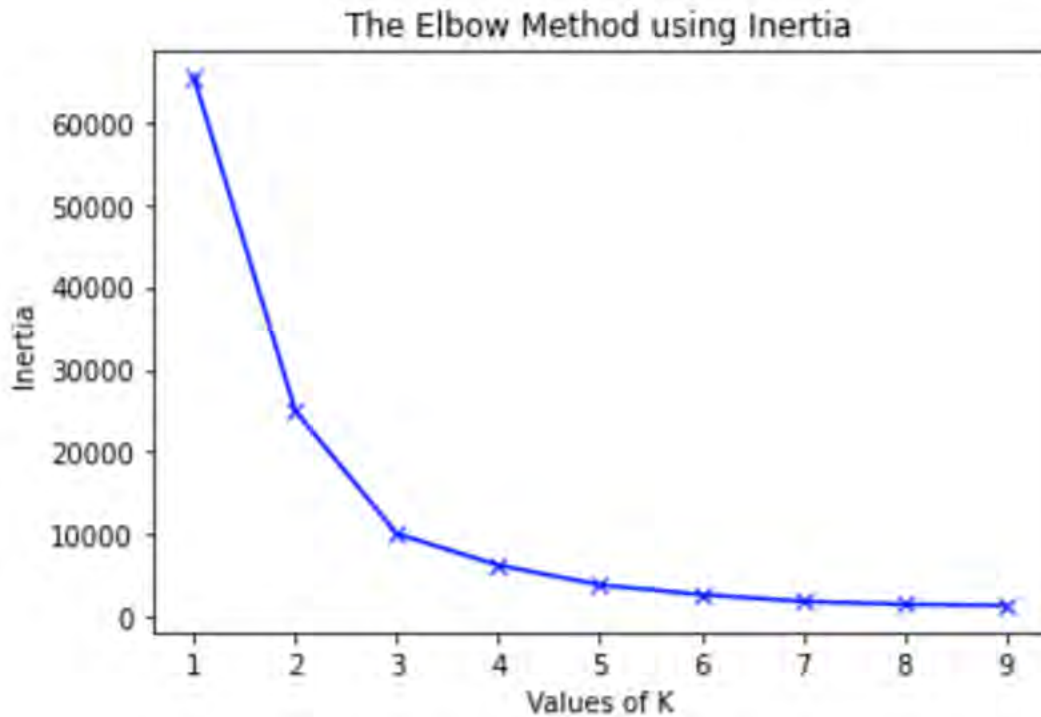


Figure 3: **Elbow Method.** The elbow method is used to determine the parameter  $K$  in K-Means Algorithm. In this figure, the WCSS starts to flatten at  $K = 4$ . Thus, the most cost-efficient quantity of clusters is 3.

I decided to find industry centers for each industry through each decade and define peer companies based on information on industrial centers.

The k-Means algorithm is used to generate industry centers. The K-means algorithm is a widely used clustering algorithm to group data into clusters based on the similarity of features. The algorithm starts from  $K$  random assigned centers, and each data point is assigned its nearest "center", forming temporary clusters. Then the algorithm updates the centers of each cluster by calculating the weighted average of the features of data points in this cluster. The algorithm iterates the assignment and updates until the centers no longer change significantly. In this study, companies' longitude and latitude coordinates are used as features in this clustering task. Compa-

nies' assets are used as weights to update cluster centers. Specifically, the parameter  $K$  is decided by a popular technique Elbow Method. It plots the within-cluster sum of squares (WCSS) against the number of clusters and looks for the "elbow" point in the curve, where the rate of decrease in WCSS starts to flatten out, see fig. [3](#)

Since companies emerge and stop operating, the geographic distribution of companies in the same industry tends to vary a lot. Thus, I generate industrial clusters and centers for different industries in different decades. As three decades and 11 industries (except industry "Other") are involved in this study, 33 cluster tasks were operated, see fig. [4](#). fig. [5](#) shows the cluster details of the manufacturing industry in the decade 1980. The small colored dots are companies in the manufacturing industry in the 1980s. Dots of the same color are in the same cluster. The dark blue dots represent cluster centers while the red dots represent scandalous firms in the manufacturing industry in the 1980s

Based on the clustering result, company performance data were classified into 2 groups: peer companies and non-peer companies. Peer companies are those that belong to the same industrial cluster as a company that has been involved in misconduct within the same decade. Then, I define a dummy variable "Peer" as the interaction term of treatment group identity and exposure to the treatment. That is, "Peer" = 1 if the observation is a peer company of the scandalous firm and in a year after the fraud announcement of the scandalous firm but within the same decade. Otherwise, "Peer" = 0. This means the performance data of companies outside the specific industrial cluster the corporate misconduct is treated as a non-peer company.

Variable Name	Formulation	Data Source
<i>ROA</i>	$NI/AT$	CompuStat
<i>ROE</i>	$NI/CEQ$	CompuStat
<i>CTA</i>	$CH/AT$	CompuStat
<i>Leverage</i>	$DLTT/CEQ$	CompuStat
<i>PRCC</i>	NA	CompuStat
<i>AnnRET</i>	$(\prod_i^{12}(1 + RET_i))^{\frac{1}{12}} - 1$	CRSP
<i>AnnRETX</i>	$(\prod_i^{12}(1 + RETX_i))^{\frac{1}{12}} - 1$	CRSP

Table 1: **Variable List.** Variable Used in Analysis.

### 3.3 Variable Definitions

To examine the spillover effect from both accounting level and financing level, I collected performance data from Compustat and CRSP Monthly Stock. The raw data collected from Compustat and CRSP include: *NI* (Net Income), *AT* (Total Asset), *CEQ* (Common Equity), *CH* (Cash), *DLTT* (Long-term Debt), *PRCC* (Close Stock Price), *RET* (Monthly Return), and *RETX* (Monthly Return without Dividend). These raw data were used to calculate more performance measurement for further analysis.

For the accounting level, I mainly investigate ROE (return on equity) and ROA (return on assets). For the financing level, I mainly investigate cash-to-asset, leverage ratios and stock prices. Also, annual returns were annualized using the monthly stock return data from CRSP Monthly Stock Database.

In table [1](#), the performance variables generated from CompuStat and CRSP are presented. Besides, this project used differential terms of ROE, ROA, CTA, leverage, and stock price to better evaluate the impact of corporate misconduct.

<b>Variable</b>	<b>N</b>	<b>Mean</b>	<b>St. Dev</b>	<b>Min</b>	<b>Max</b>
<i>AT</i>	87201	2676.87	8546.96	3.07	64126
<i>EMP</i>	81847	6.98	17.78	0	121.63
<i>cash_to_asset</i>	87201	0.08	0.11	0.0004	0.58
<i>Leverage</i>	87201	0.68	1.11	0	7.42
<i>ROE</i>	87201	0.15	0.14	0.004	0.97
<i>ROA</i>	87201	0.06	0.06	0.001	0.32
<i>PRCC</i>	87201	21.08	17.41	0.5	90.78
<i>ANN_RET</i>	87201	0.22	0.58	-0.75	2.98
<i>ANN_RET_X</i>	87201	0.20	0.58	-0.75	2.97
<i>DTIC</i>	20527	23.18	23.85	0.60	159.29

Table 2: **Summary Statistics.**

### 3.4 Summary Statistics

Based on the performance data definition, industrial cluster generating logic, and definition of peer companies, a 3-dimensional data set is framed for further analysis. Each performance record is featured by 3 indexed: industrial cluster feature, time feature, and peer feature. Besides the performance data, a variable Distance-to-Industry-Center of the scandalous firm (DTIC) is added to the data set to measure how DTIC affects the magnitude of the spillover effect. The whole data set is later divided into two groups: groups with large DTIC and groups with small DTIC. Peer firms affected by corporate misconduct which has a DTIC smaller than the mean DTIC is grouped as small DTIC. The group division is used in data analysis part for subset regression analyses.

All continuous performance variables were winsorized to reduce the impact of outliers. The lowest 1% and highest 1% were winsorized to the 1% percentile or the 99% percentile. The Table 2 summarizes the detailed statistics of all variables.

## 4 Methodology

In this section, I will provide a detailed description of the methods used in our study, including the descriptive data analysis methods and DID (Difference-in-Difference) Regression model.

### 4.1 Descriptive Analysis

The goal of a descriptive analysis is to summarize the basic features of a data set by using statistical methods. With descriptive analysis, it is easy to identify patterns and trends in the data, gaining a better understanding of the variables under study. In this project, I summarized the mean and standard deviation of each performance variable for the group peer companies and non-peer companies. Then, an unpaired t-test was conducted for each performance variable to see whether there were significant differences between groups. Additionally, the whole data set was split into two groups based on the DTIC of misconduct events. Performance differences between two DTIC subsamples were also compared to see the pattern.

### 4.2 DiD Regression

The Difference-in-Difference (DiD) regression is a widely used statistical method to examine the impact of a treatment. It estimates the impact by comparing the difference of dependent variables between treated groups and control groups over time. One requirement for using DiD analysis is to identify the treatment and introduce the treated group and controlled group. The DiD regression commits to the "parallel assumption," which assumes that the trend of the dependent variable before the event is the same for both the controlled group and the treated group.

In this research project, as the natural treatment is the occurrence of corporate

misconduct, peer companies were considered as a treated group while the non-peer companies were considered as a controlled group. The performance data were treated as dependent variables and the DiD regressions were used to identify the difference of performance data between the two groups. As the data set is featured by both time and industrial clusters, I assumed that the trend within the same industrial cluster over time is the same.

Equation (1) illustrates the DiD regression model used in this project. To specify the subscription of each term,  $i$  represents the industry while  $c$  represents each cluster.  $t$  holds for the time. The term  $Peer_{ict}$  is the dummy variable of interest indicating whether one specific performance record is a peer company of the scandalous firm and in a year after the misconduct event. The term  $B_t$  controls the time-fixed effect while the term  $X_{ic}$  controls the industrial cluster fixed effect. By controlling the two-dimensional fixed effect,  $\beta_1$  indicates the difference in performance variables between the two groups.

$$Y = \beta_0 + \beta_1 Peer_{ict} + \beta_2 B_t + \beta_3 X_{ic} + \epsilon_{ict} \quad (1)$$

Along with the regression analyses on the whole data set, some subset regression analyses were conducted. Subsets were split based on the degree of distance-to-industry-center (DTIC) to examine whether misconduct of large DTIC and misconduct of small DTIC will pose different effects on peer companies' performance.

## 5 Results

In this section, I compared several performance variables of peer companies and non-peer companies to investigate the impact of corporate misconduct. Firstly, descriptive



analyses were conducted to find out patterns in the differences between peer firms and non-peer firms. Secondly, OLS regressions were conducted. All performance variables were used as dependent variables while the dummy indicator *peer* was used as the independent variable. *AT* and *EMP* were considered to represent companies' features and used as controlled variables. Moreover, the Difference-in-Difference regression (DiD) showed the impact of corporate misconduct on the two different groups. The treated group was the peer company group while the controlled group was the non-peer company group.

## 5.1 Descriptive Analysis

The descriptive analysis of performance variables is shown in the table [3](#) and table [4](#).

### 5.1.1 Full Sample

The analysis data indicates that the peer firms were negatively affected by corporate misconduct as the significant differences showed. For cash holding, peer companies tended to hold less cash, indicating lower flexibility. At the accounting level, both the roa and roe of peer companies are lower than their non-peer counterparts. However, for the finance front, there were no significant differences in annual stock return while the year-end stock prices of peer firms were even higher than those of non-peer firms. This may be because of the competitor rivalry power, which makes peer companies even benefit from the corporate misconduct. Furthermore, the analysis reveals that peer companies have a relatively higher leverage level, indicating a higher debt burden caused by corporate misconduct within the industry and geographic area.

	Peer			Non Peer			Diff.	T
	Mean	Std	Count	Mean	Std	Count		
cash_to_asset	0.074	0.106	19127	0.080	0.111	67675	-0.006 ***	-7.265
leverage	0.707	1.187	19127	0.668	1.073	67675	0.039 ***	4.139
roe	0.143	0.127	19127	0.147	0.133	67675	-0.004 ***	-3.748
roa	0.056	0.057	19127	0.063	0.057	67675	-0.006 ***	-13.549
prcc_f	21.362	18.235	19127	21.005	17.173	67675	0.358 ***	2.424
ann_RET	0.218	0.564	19127	0.225	0.591	67675	-0.007	-1.394
ann_RETX	0.196	0.562	19127	0.204	0.590	67675	-0.008	-1.809

Table 3: **Descriptive analysis on full sample.** The table compares the performance differences between the two groups using T-Test.

### 5.1.2 DTIC Subsample

The table 4 presents the performance differences between peer firms of large-DTIC misconduct and peer firms of small-DTIC misconduct. It suggests that there are significant performance differences between the two subsamples. Specifically, peer firms of large-DTIC misconduct tend to perform better as shown by return from both accounting level and stock level. Moreover, the leverage level of peer firms of large-DTIC misconduct is lower, indicating those peer firms bear less debt burden. However, the stock price of peer firms of large-DTIC misconduct is lower.

Overall, the geographic proximity of scandalous firm to the industrial center affects the degree of spillover effect. However, without any controlled variable or fixed effect, the difference might be led by other features instead of misconduct.

## 5.2 DiD Regression

Without any controlled effect, although the patterns from descriptive analysis showed that peer firms were negatively affected by the misconduct, more analysis should be conducted to generate more comprehensive conclusion. As discussed in Section 4, DiD regressions were conducted to investigate how the performance variables of the treated group (peer companies) were different from those of the controlled group.

	Large DTIC			Small DTIC			Diff.	T
	Mean	Std	Count	Mean	Std	Count		
cash_to_asset	0.075	0.104	7398	0.073	0.108	11819	0.001	0.819
leverage	0.555	0.994	7398	0.806	1.296	11819	-0.251 ***	-15.124
roe	0.150	0.131	7398	0.140	0.130	11819	0.010 ***	4.930
roa	0.067	0.057	7398	0.050	0.057	11819	0.016 ***	19.248
prcc_f	19.482	17.402	7398	22.533	18.641	11819	-3.052 ***	-11.507
ann_RET	0.230	0.591	7398	0.209	0.546	11819	0.021 ***	2.462
ann_RETX	0.211	0.590	7398	0.185	0.544	11819	0.025 ***	2.984

Table 4: **Descriptive analysis on subsample.** The table compares the performance differences between peer firms of small DTIC misconduct and peer firms of large DTIC misconduct.

Compared with the descriptive analysis, in the regression analysis, time fixed-effect and industrial cluster fixed-effect were controlled to eliminate trends and features caused by time and industrial clusters.

Below two performance variables Return on Equity and Annual Return were detailed discussed. Three groups of regression analyses were conducted. The first group is marked by (1), (2), and (3), showing the DiD regression on the whole data set. The second and third groups, both containing three specific regressions, show how misconduct with large DTIC or low DTIC affects peer firms respectively. In the regression result tables, "at" refers to the number of total assets while "emp" refers to the number of employees. The two terms were treated as control variables to control the individual characteristics of a firm.

### 5.2.1 Return on Equity

I first looked at the spillover effect on ROE, which reflects the operation performance from the accounting level. As shown in table 5, with time fixed-effect and industrial cluster fixed-effect, the coefficients for the Peer variable are statistically significantly positive. Controlling the asset and number of employees, the coefficient for the Peer variable is still significant for the whole data. This suggests that in the general

case, peer companies will benefit from corporate misconduct from the perspective of accounting return.

However, although the coefficient is still significant in the small DTIC sub-sample, the coefficient is not statistically significant in the large DTIC sub-sample, suggesting that the spillover effect will depend on the DTIC of corporate misconduct. For corporate misconduct with larger DTIC, the spillover effect tends to be too small to make any difference between peer firms and non-peer firms. For corporate misconduct with smaller DTIC, the spillover effect is much larger, making peer companies gain more than non-peer companies.

Overall, the results suggest that peer firms located in the same industrial cluster as the scandalous firms experience a positive gain in financial performance compared to non-peer firms after the announcement of the misconduct. Additionally, the small DTIC will strengthen the positive spillover effect.

### **5.2.2 Annual Return**

The regression results in Table 6 show the difference of impact on the annual return between peer firms and non-peer firms. The annual return is the compounded monthly stock return, showing the public valuation and expectation of the firm. The coefficient for the variable "Peer" is positive, but it is not statistically significant on the whole data. In a DiD regression model, this means the annual stock return of peer companies and non-peer companies does not differ significantly and this indicates that the presence of corporate misconduct does not significantly affect the public expectation and valuation on peer firms.

Although for the whole data set and large DTIC sample, the coefficient for variable "Peer" is not significant, the coefficient for variable "Peer" in the analysis for the small DTIC sample is significant. This indicates that if the corporate misconduct was near

the industrial center, a spillover effect exists and peer companies in the same industrial cluster will benefit from the misconduct. However, if corporate misconduct happens far away from the industrial center, the spillover effect will be too small to be detected.

## 6 Conclusion

In conclusion, this thesis provides a comprehensive investigation of how geographic concentration affects the corporate misconduct spillover effect. Starting from a sample of 772 misconduct events, this study categorized firms based on industrial clusters and time. Although Descriptive analyses suggest a negative spillover effect, regression analyses study show that peer firms located in the same industry center as the scandalous firms experience a positive gain in financial performance compared to non-peer companies after the announcement of the misconduct.

The study uses the K-means algorithm to determine the industrial cluster, which is both statistically logical and economically logical. Performance data from both the accounting level and the financing level were used to measure the spillover effect of misconduct events. Performance record before the misconduct announcement or outside the industry cluster of the misconduct event is categorized as non-peer firm. The performance record of the same industrial cluster after the misconduct announcement year is treated as a peer firm.

Peer firms were considered as the treatment group and non-peer firms were considered as the controlled group. Descriptive t-tests and DiD (difference-in-difference) regressions were conducted to examine the performance difference between the two groups. Although descriptive analyses show a negative spillover effect, the DiD regressions show a positive gain from misconduct events. As the DiD regressions controlled firm characteristics, time, and industrial clusters, the negative effect from descriptive

analyses may be led by those uncontrolled effects. Additionally, sub-sample t-tests and sub-sample regressions indicate that small DTIC will contribute to the intensity of the spillover effect.

A possible reason for the positive effect is that peer firms gain from the competitor's rivalry power. When a company is involved in misconduct, the other peer companies have fewer competitors, thus getting more market share. Since the industrial center is generated by a weighted average method of all firms' locations using assets as weights, the geographic proximity to the industrial center indicates the importance of the industrial cluster. Thus, if the DTIC is smaller, the misconduct announcement indicates the loss of a bigger competitor. However, the misconduct event can also lead to a reduction in public trust, thus causing the decline of the whole industry. Due to the lack of time, the study did not examine the extent of the positive effect and the negative effect. Further study could focus on a detailed examination of the reason for the positive pattern.

The study contributes to the literature by shedding light on both geographic and industrial identity. The insights show that involving both dimensions is significant for further research on corporate misconduct. Additionally, the study uses a large sample of misconduct events to investigate the spillover effect while similar researches tend to use case study.

Overall, this study provides valuable insights into the complex relationship between industry geographic concentration and the spillover effect of corporate financial misconduct. Further research could explore additional performance measurements to investigate the spillover effect and geographic concentration.

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Figure 4: **Cluster.** Since three decades and 11 industries are involved in this study, 33 clustering tasks were operated.

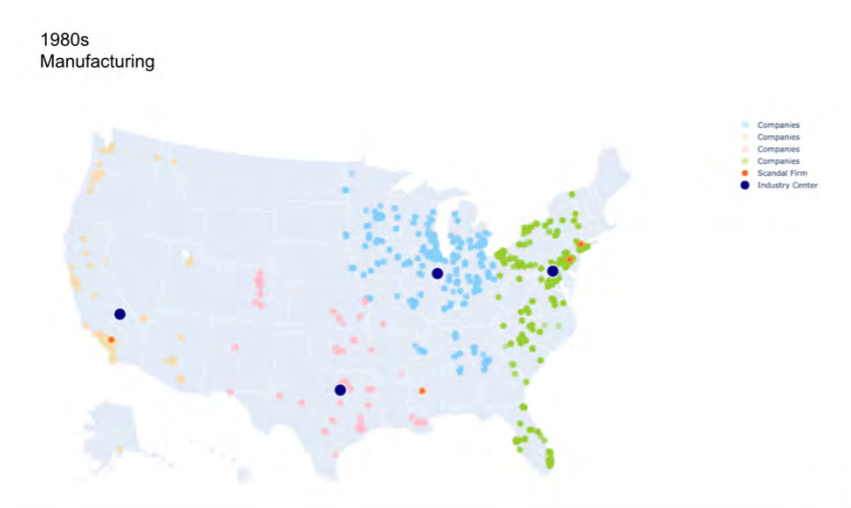


Figure 5: **1980s Manufacturing Cluster.** The small colored dots are companies in the manufacturing industry in the 1980s. Dots of the same color are in the same cluster. The dark blue dots represent cluster centers while the red dots represent scandalous firms in the manufacturing industry in the 1980s.

	ROE								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full Sample	Full Sample	Full Sample	Large DTIC	Large DTIC	Large DTIC	Small DTIC	Small DTIC	Small DTIC
Sub-Sample									
Intercept	0.177 *** (0.007)	0.178 *** (0.009)	0.191 *** (0.010)	0.181 *** (0.011)	0.186 *** (0.013)	0.192 *** (0.016)	0.127 *** (0.008)	0.120 *** (0.012)	0.130 *** (0.014)
Peer	0.011 * (0.005)	0.011 * (0.005)	0.012 * (0.005)	-0.001 (0.005)	-0.002 (0.005)	0.003 (0.007)	0.024 * (0.011)	0.024 * (0.011)	0.017 . (0.009)
Log(at)		-0.0004 *** (0.001)	-0.003 * (0.001)		-0.002 (0.002)	-0.004 * (0.002)		0.002 (0.002)	-0.001 (0.002)
Emp			0.001 *** (0.0001)		0.001 *** (0.0001)	0.001 *** (0.0001)			0.0004 * (0.0002)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industrial Cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Standard Error	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster

Table 5: DiD Regression on ROE. The table presents the regression result when ROE is the dependent variable.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	Full Sample	Industrial Cluster	Full Sample	Industrial Cluster	Full Sample	Industrial Cluster	Large DTIC	Industrial Cluster	Large DTIC	Industrial Cluster	Large DTIC	Industrial Cluster	Small DTIC	Industrial Cluster	Small DTIC	Industrial Cluster	Small DTIC	Industrial Cluster
Sub-Sample	0.427 ***	Yes	0.457 ***	Yes	0.435 ***	Yes	0.37 ***	Yes	0.384 ***	Yes	0.342 ***	Yes	0.016 ***	Yes	0.193 ***	Yes	0.0203 ***	Yes
Intercept	(0.042)	Yes	(0.043)	Yes	(0.043)	Yes	(0.079)	Yes	(0.085)	Yes	(0.058)	Yes	(0.006)	Yes	(0.026)	Yes	(0.021)	Yes
Peer	0.014		0.013		0.016		-0.030		-0.030		-0.020		0.051 .		0.05 .		0.041 .	
	(0.036)		(0.036)		(0.036)		(0.038)		(0.038)		(0.037)		(0.028)		(0.027)		(0.025)	
Log(at)	-0.008 ***		-0.008 ***		-0.005 *				-0.005		0.002				-0.006		-0.008	
	(0.002)		(0.002)		(0.003)				(0.004)		(0.005)				(0.005)		(0.004)	
Emp	0.001 ***	Yes	0.001 ***	Yes	0.001 ***	Yes	-0.001 ***	Yes	-0.001 ***	Yes	-0.001 ***	Yes						
	(0.0001)	Yes	(0.0001)	Yes	(0.0001)	Yes	(0.0003)	Yes	(0.0003)	Yes	(0.0003)	Yes						
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industrial Cluster Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Standard Error	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster	Industrial Cluster

Table 6: DiD Regression on `ann_RET`. The table presents the regression result when `ann_RET` is the dependent variable.