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ESSAYS IN APPLIED MICROECONOMICS

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ABSTRACT

This dissertation consists of three chapters concerning topics in applied microeconomics. In Chapter 1, I investigate the impact of the 1960s riots on an individual's choice to return to the South following the Great Migration. Using the 1980 5% IPUMS data and Carter's (1989) extraordinary data collection of the 1960s riots, I find a significantly negative correlation between riots severity and mobility for both white and blacks. Following Collins and Margo's (2007) instrumental variable strategy, I exploit exogenous variations in rainfall in April 1968, during which hundreds of riots broke out after the assassination of Martin Luther King Jr. Using rainfall as an instrumental variable, I find a negative causal effect of riot severity on the likelihood of return migration to the South.

In Chapter 2, using a unique dataset of retracted papers collected by Retraction Watch, I investigate the factors associated with the time to retraction and the reasons for retraction. I find that the number of authors positively correlates with time-to-retraction. Papers with at least one author that is affiliated with a US institution have a longer time to retract and are more likely to be revealed with clear reasons for retractions. The number of fields is negatively correlated with time-to-retraction, while the number of subjects is positively correlated with it. Compared to papers in social sciences, papers in environmental sciences and business and

technology take less time, while papers in humanities take longer to retract. Papers in basic life sciences and business and technology are more likely to be retracted for "ugly" reasons instead of good reasons, while papers in health sciences are less likely to be retracted for bad or "ugly" reasons instead of good reasons, compared to papers in social sciences. Interestingly, having at least one author who is affiliated with a university decreases the probability of having a clearly stated reason for retraction. In addition, the publication year is negatively correlated with time-to-retraction, suggesting that either the speed of discovering false science or the speed of responding to mistakes in papers (or both) has increased over the years. Using a DID framework, I find retraction decreases the annual citations received by papers, and the impact is greater for papers that are retracted due to severe misconduct than those with milder mistakes or unknown reasons.

In Chapter 3, I extend the results in Chapter 2 and investigate further the relationship between retractions and citation patterns, focusing on citation sentiments. Using a unique collection of citation contexts of the citing papers to the retracted and control papers, and a state-of-art rule-based model, I show that there is a sharp increase in explicitly negative citations and a moderate increase in implicitly negative citations for retracted papers before retractions. While implicitly positive and neutral citations increase slightly for retracted papers before retraction, their explicitly positive citations drop sharply before retractions. Through a staggered DID framework, I also provide causal evidence that retractions lead to decreases in all types of citations by sentiments.

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LIST OF ABBREVIATIONS

COPE	Committee on Publication Ethics
DID	Difference-in-Difference
DOI	Digital Object Identifier
IV	Instrumental Variable
MMR	Measles, mumps, and rubella
MNL	Multinomial Logit
TWFE	Two-Way Fixed Effects
OLS	Ordinary Least Squares
PPML	Poisson Pseudomaximum likelihood
US	United States
2SLS	Two-Stage Least Squares

CHAPTER 1

Impact of the 1960s Racial Riots on Return Migration

1.1 INTRODUCTION

During the Great Migration, 7 million African Americans moved from the South to the North, and as a result, the racial landscape of the US changed dramatically. The increasing presence of the black population in the North has also transformed the racial dynamics in the country. Many scholars have looked at the causes and consequences of the Great Migration, but we know little about whether the people who moved to the North stayed or returned. Meanwhile, hundreds of racial riots broke out during the 1960s across the country, mainly in the North. Unlike the previous episodes of racial violence that involved mainly the persecution of blacks, these riots mostly involved violent clashes between black civilians and white police, looting, and arson of establishments. It is intriguing to ask what the impact of the 1960s racial riots was on people's decision to move, especially southern-born migrants' decisions to return to the South.

In this paper, I use Carter's (1986) comprehensive data collection of racial riots from 1964 to 1971 and the 1980 US Census data to study the impact of the 1960s racial riots on return migration decisions between 1975 to 1980. Following Collins & Margo (2007), I use rainfall in April 1968 as an instrumental variable to estimate the causal impact. I show that higher riots severity in the 1960s racial riots leads to a lower probability of return migration for southern-born migrants, even conditional on moving to other states. This pattern is also true for northern-born blacks and whites. In addition, northern-born white individuals in cities experiencing more severe riots were likely to move to other cities in their states.

These results enrich the Great Migration literature by investigating the reason for the return movement in the 1970s through rigorous economic analysis. This paper also sheds light on the impact of racial riots on people's migration decisions. While this paper does not provide direct empirical evidence for the mechanism of the impact, the results suggest some possible explanations. The economic damage caused by the riots may constrain their ability to move far since riot severity reduces peoples' probability of both moving to other states and to the South. The riots might also remind people of the racial tension and make them avoid going to the South, where used to be intense persecution of blacks.

The rest of the paper is organized as follows. Section 2 provides background information and a review of related literature on the Great Migration and the 1960s racial riots. Section 3 introduces the datasets I use for my analysis. Section 4 specifies in detail the empirical models I employ. Section 5 presents the results of my analysis and discussions on them. Section 7 concludes the paper.

1.2 BACKGROUND

1.2.1 The Great Migration

The return movement I study in this paper took place in the context of the Great Migration (1910-1970), one of the most important episodes in recent American migration history. During the 20th century, the racial landscape of the US changed dramatically. In 1910, 50 years after the Emancipation Proclamation, 86% of African Americans still lived in the South. From 1915-1970, 7 million black migrants moved from the rural South to mostly the urban North. By 1970, the majority of black residents lived outside of the South. Since the 1970s, there have been growing southern-bound migration waves. These shifts reflect profound social and economic changes and have a lasting impact on the racial dynamics of the country. Many economists and sociologists have studied various aspects of the Great Migration, including the causes of the event, the selection of migrants and returns to migration, and the impact of in-migration on the local conditions in the north. We know relatively less about whether people who moved to the North stayed or returned and the factors affecting their decisions to return.

Many scholars have investigated the pull and push factors that drove people from the South to the North. Using the census data from 1910 to 1930 and county-level lynching data, Tolnay & Beck (1992) found that blacks were more likely to leave places where a lynching took place more frequently. Carrington et al. (1996) presented a dynamic model that characterizes declining moving costs of migration with the stock of migrants. They find that the boll weevil and WWI catalyzed the migration process. Collins (1997) employed state and city-level census data from 1880 to 1950 and used the proportion of the existing foreign-born population as an instrument for foreign migration flow to establish a plausibly negative causal relation between European immigration and black migration from the south. Specifically, he argued that the Great Migration was triggered by the sharp decline in European immigration. In addition, Lange et al. (2009) used new county-level panel data to generate estimates of the time path of the effects of the boll weevil on the southern economy from 1892 to 1932. They find that crop damage caused by weevils leads to significant out-migration. Similarly, using census data and county-level agricultural data from various sources, Boustan et al. (2010) found that the county-level out-migration from the south was affected by variations in several local agricultural conditions, which then became useful first-stage instrument variables for migration flow in her analysis of white flight in the north. These findings reveal the motivation for southerners to leave their hometowns and head to new lands with better social and economic conditions. It is then curious to see if the migrants would return to their southern home when the conditions changed or even reverted. My study exploits exogenous changes in racial dynamics measured by racial riot intensity to shed light on migrants' decisions and attitudes toward migration.

More sociologists than economists have documented the return migration to the south closely. Using the 1960 and 1970 census data, Long & Hansen (1975) explored the trends in return migration to the south and the importance of return migration relative to other types of movement. They discovered that blacks had a higher proportion of return migrants out of all migrants moving south than whites using data from the 1960s and 1970s. Also, among return migrants, blacks were more likely to return to their birth states. In a related study, they investigated the selectivity of black male return migrants with descriptive statistics from the same census data (Long & Hansen, 1977). They found return migrants were more educated than both the southern-born migrants staying in the north and the southerners who had never migrated to the north in every age group above 25 years old in both census periods. My paper provides empirical evaluations of the southern-bound return movement, with a breakdown by race and types of movement in the aftermath of racial riots. Also, riots made people less willing to move since they decided to stay fighting and hope for improvement as the government responded to the riots.

1.2.2 The 1960s Racial Riots

While the Great Migration reformed racial landscapes across the country, the racial dynamics of black and white races gradually evolved. During the 1960s, hundreds of racial riots broke out across the US, mainly in the northern cities. These events were unprecedented in American history, both in terms of the large numbers and their unusual nature. Before the 1940s, most racial riots involved whites attacking blacks. On the contrary, the 1960s racial riots, as well as the 1943 riots with a much smaller number of events, were violent clashes between black civilians and white police, looting, and arson of establishments (Collins & Margo, 2007). Since they took place mostly in the North and were followed by an increasing trend of southern-bound migration, it is intriguing to see the impact of the riots on people's decision to move.

Many sociologists and economists have studied the causes of the 1960s riots. Lieberson & Silverman (1965) employed data from 76 racial riots in the US between 1913 and 1963 and provided descriptive observations that cities with poor institutional and governmental abilities to resolve preexisting racial problems are more likely to experience riots. Using statistical models, Spilerman (1970; 1971; 1976) found that differences in riots-proneness across cities do not explain the variations in locations and severity of the 1960s riots, after controlling for the size of the black population and region. He showed empirical evidence that the various sources of disappointment to the black population can explain the variations in riot outbreaks in the non-South. Carter (1986) enriched Spilerman's data by extending it for more years and adding the 1968 Kerner Commission's 15-Cities Study to show that there was no correlation between black subjective grievances and racial riots. Extending Spilerman's work by including riots data from 1954 to 1993, Olzak et al. (1996) found that racial segregation combined with racial competition tends to increase the rate of racial riots. They also showed statistical results that prior history of racial turmoil leads to more racial riots later. Furthermore, DiPasquale & Glaeser (1998) employed 1960s riots data and the 1992 Los Angeles riot to present econometric evidence that the opportunity cost of time and potential punishment affect the occurrence and intensity of riots. Myers (1997; 2000) found empirical evidence that cities have different susceptibility to the diffusion of riots, in which mass media plays an important role.

Some scholars have also investigated the consequences of the riots. In a study investigating the reasons for "white flight" from large cities to suburban areas, Frey (1979) presented empirical evidence that the 1960s riots had no significant correlation with the out-movement of the white population from 1965 to 1970. Using riots and government expenditure data in the late 1960s, Welch (1975) conducted descriptive statistics to show a greater increase in expenditures related to black and white demand in cities that experienced riots than in other cities, after controlling for many cities and government characteristics. More recently, using the census data and Carter's riots data and by constructing two plausibly exogenous instrumental variables, Collins & Margo (2007) found that the1960s riots led to decreases in black-owned property values between 1960 and 1970, and widened the racial gap in housing values in riots-affected cities during the 1970s. In addition, using the same instrumental variable strategies, Collins & Margo (2004) showed that the riots also adversely affected family income and male employment.

This paper looks at the consequences of these riots on people's decision to migrate, especially to the South. Theoretically, the direction of influence is unclear. On the one hand, while the riots led to a deterioration of northern cities and destabilized the affected areas, migrants may decide to go 'home'. In addition, riots may cause financial constraints preventing people from moving. On the other hand, riots may accelerate the changing dynamics of racial interactions, encouraging migrants to stay to fight and hope for a better future. It is, therefore, an empirical inquiry into the impact of the 1960s racial riots on migration decisions in the 1970s. Using data on the riots and migration, I investigate this influence empirically through an instrumental variable approach.

1.3 DATA

1.3.1 Migration Data

A unique set of questionnaires in the US census data allows me to identify return migration in the US. The questionnaires ask where people lived five years ago prior to the time of the survey. A person is considered a return migrant if he or she was born in the south, lived in the north five years ago, and currently lives in the south again. In particular, using the 1980 5% US census data, I can observe people's cities of residence in 1975. I am also able to identify people who stayed in the same house, moved within the city, moved within the state, moved between the states, and moved between regions from 1975 to 1980. For people who were outside their birth states/regions in 1975, I can also identify if they returned to their birth states/regions in 1980. It is noteworthy that such a definition only provides a rough estimation of short-term movement since I only observe individuals' locations in 1975 and 1980.

Following the consensus in the Great Migration literature, I define the following states as the South: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, South Carolina, Tennessee, Texas, Virginia, and West Virginia. This differs from the region definition used in the Census. Specifically, the District of Columbia, Delaware, and Maryland are not included in the South because they experienced net in-migration of the black population in the twentieth century (Boustan, 2017; Kirby, 1983). States that are not in the South are considered as the northern states, which are further divided into the West, the Midwest, and the Northeast according to the Census definitions. I also obtain various individual characteristics as covariates from the census data. They include age, years of schooling, number of children they have, race, and gender. I confine the sample to people with available migration information on cities where people stayed five years ago, denoted by the variable *migcity5*. Using this dataset, I computed aggregated city population, the proportion of the black population, and the proportion of people born in the South in 1975 for all cities listed under the variable *migcity5*.

1.3.2 The 1960s Riots Data

For information on the 1960s racial riots, I use data collected by Carter (1986), which is an extended and verified dataset from Spilerman's (1970; 1971; 1976) original data. It contains dates and locations of 753 riot incidents from 1964 to 1971, including the number of arrests, injuries, the occurrence of arson, deaths, and duration of the riots. I use these features to compute severity measures, which I describe in the next section. The dataset follows Spilerman's original working definition of riots, which requires the riots to have at least 30 participants, some of whom need to be black and to result in aggressive behavior. It leaves out cases of disturbances that occurred in school and organized Civil Rights protests. Table 1.1 shows the top five riots by severity in the data. Carter's dataset has been considered a comprehensive record of riots across the country in those years (Collins & Margo, 2007). I then combine these migration and riot datasets by assigning the city severity index to the cities where people resided five years ago in the 1980 5% census data. In total, 129 cities show up only in the riots data but not in the census data. I dropped them since I do not have migration information for them. For cities that only show up in the census data but not the riots data, I assume they did not experience any riots in the 1960s.

Table 1.1: Top Five Riots by Severity

Date	Location	Precipitating Event
July, 1967	Detroit, MI	Police raid of an unlicensed, after-hours bar blind pig.
August, 1965	L.A., CA	Black motorist on parole for robbery pulled over for reckless driving.
April, 1968	Washington DC	Assassination of Martin Luther King, Jr.
July, 1967	Newark, NJ	Two Newark Police officers arrested and beat a black taxi driver.
April, 1968	Chicago, IL	Assassination of Martin Luther King, Jr.

1.3.3 Weather Data

To address the problem of endogeneity in my analysis, which I discuss in the next section, I collect and use a set of weather data for the instrumental variable approach. I obtained city-level average monthly precipitation in April 1967 and April 1968, as well as average annual precipitation over 1960-1980 from National Oceanic and Atmospheric Administration, "Climate Data Online". I then combine them with the aforementioned matched dataset for my empirical analysis.

1.4 EMPIRICAL STRATEGY

1.4.1 Measures of Riot Severity

To obtain a measure of the severity of the riots, I follow Collins and Margo's (2007) strategy to construct a severity index, which combines the five components of riot severity mentioned above. In particular, the index for each riot is the sum of the relative damages as a proportion of the total damages for all riots. Each city is then assigned the sum of indexes of all riots in the city. The formula for computing the severity index of city j is shown below:

$$Severity_j = \sum_{r \in \Omega_j} (\sum_k \frac{X_{kr}}{X_{kR}}) \tag{1.1}$$

where

$$X_{kR} = \sum_{r \in \Omega} X_{kr}$$

X_{kr} is the characteristics k of riot r (for example, deaths caused by riot r) and X_{kR} is the sum of this characteristic across all riots in the sample (for example, total deaths caused by all riots). In the equation, Ω is the set of all riots, and Ω_j is the set of riots in city j. Fourty cities show up only in the census data but not the riots data. I assign value 0 to the city riot severity index for these cities since it's reasonable to consider Carter's dataset as a comprehensive record of riots across the entire country in those years.

The distribution of the severity index is highly skewed, with a large group of cities having low indexes. Inspired by the approach used in Collins and Margo (2007), I regroup cities in my final sample into three categories: low severity, medium severity, and high severity. The low severity category includes cities with an index below 0.009 (the 28th percentile); the medium severity category includes cities with an index between 0.009 and 0.07 (the 28th to 59th percentile); and the high severity category includes cities with an index between 0.07 to 0.52 (above the 59th percentile).

1.4.2 Correlations between Riots and Migration

To understand the migration patterns between 1975 and 1980 and how it has been affected by the 1960s riots, I mainly investigate three sets of specifications. I begin by looking at the relationship between the riots and people's decisions to move between 1975 and 1980 in general. The sample includes all non-schooling 30-50-year-old individuals in my merged dataset. Specifically, I first estimate the simple specifications by Ordinary Least Squares (OLS):

$$M_{ij} = \beta Severity_j + \Omega X_{ij} + \Sigma X_j + BPL_i + e_{ij} \tag{1.2}$$

Individuals are indexed by i and the cities where people stayed in 1975 are indexed by j. M_{ij} is a dummy variable indicating the movement by individual i who lived in city j in 1975. This includes moving at all (not seen in the same household), moving within the city j, moving to other cities in the states, moving to other states in the region, and moving to other regions from 1975 to 1980. $Severity_j$ is the riots severity index for city j. X_{ij} is a vector of individual characteristics including age at 1975, age at 1975 squared, gender, and a dummy for having any children that are under age 5 in 1980, and X_j is a vector of city characteristics including total population, percent black, and percent southern-born in 1975. BPL_i is the birth state fixed effect. The parameter of interest is β.

I then move on to investigate the relationship between riots and people's decisions to move "home", i.e. places where they were born. To do this, I narrowed my sample to individuals who, in 1975, lived outside of the state or region where they were born. I also excluded non-US-born individuals as they would certainly not return home in 1980 by the construction of the census data.

These first two sets of specifications will shed light on the extent of migration and home-bound movement in general, which naturally leads to the last set of investigations focusing on the population affected by the Great Migration. I will narrow my sample to all non-schooling 30-50-year-old individuals who were born in the South and lived in the North in 1975. In theory, they could have moved at any time after birth and could have moved to other places before 1975. Given that they aged from 30 to 50 years ago, I assume they participated in the Great Migration, which lasted from 1915 to the 1970s. I estimate the following basic specification by Ordinary Least Squares (OLS) model takes the following form,

$$Return_{ij} = \beta Severity_j + \Omega X_{ij} + \Sigma X_j + BPL_i + e_{ij} \tag{1.3}$$

where $Return_{ij}$ equals 1 if individual i who lived in city j in 1975 were in the South in 1980, and 0 otherwise. The parameter of interest is also β. Other variables follow the same notations as in equation 1.2.

1.4.3 Instrumental Variable Approach

The OLS specification suffers from the problem of omitted variable bias since there could be unobserved characteristics that affect both riots severity and migration decisions. Even though the migration decision took place after the outbreaks of riots, there may be unobserved city-level and individual-level characteristics that affect both the likelihood of racial riots and return migration. For example, strong racial tension in a city may make riots more likely to happen and, at the same time, make the city less desirable for blacks to stay. This would lead to an upward bias in β.

To solve this issue, I follow Collins and Margo (2007)'s instrumental variable approach and propose the following Two-Stage Least Squares (2SLS) model. The first stage is at the city level with the following specification:

$$Severity_j = \theta PRCP_j + \Gamma X_J + Region_j + \epsilon_j \tag{1.4}$$

where $PRCP_j$ is the average monthly precipitation in April 1968, and $Region_j$ is the Census region to which city j belongs. The second stage is at the individual level specified as:

$$Return_{ij} = \beta Sever\hat{i}ty_j + \Omega X_{ij} + \Sigma X_j + BPL_i + \nu_{ij} \tag{1.5}$$

I instrument riot severity using rainfall in the month of April 1968. Martin Luther King Jr. was assassinated on April 4, 1968, and subsequently, more than 100 riots took place. There is considerable anecdotal evidence that people are less likely to participate in collective violence when it rains. For example, as cited by Collins and Margo, the New York Times kept the streets empty after two days of riots in Miami on 10 August 1968. In August 1969 the New York Times cited that rainfall had "nipped one riot in the bud" by a community activist in Washington (Collins & Margo, 2007). Rainfall is highly relevant to the process of rioting, and riots after the assassination of Martin Luther King Jr. constitute a large proportion of my riot data, generating variations in the severity index across cities. Therefore, the rainfall in April 1968 is highly relevant to the riot severity level experienced by cities. With the instrumental variable, I provide plausibly causal estimates on the impact of the 1960s racial riots on migration decisions between 1975 and 1980.

1.5 RESULTS

1.5.1 Descriptive Statistics

Table 1.2 shows the summary statistics at the city level by the three categories. The mean severity index at low, medium and high severity categories are 0, 0.02, and 0.2. Cities with higher severity indexes have larger total and US-born populations. Cities in the high-severity category had the largest mean total population in 1975, with the largest fraction of foreign-born populations. The black proportion of the population is also increasing in riot severity, with the high-severity category having a black proportion that was more than 3 times larger than that in the low-severity category. This is consistent with our understanding of the contexts and causes of the 1960s riots. Cities in different regions experienced different levels of riot severity. About 93 percent of the cities in the high-severity category belong to the North (50 percent in the northeastern region). Southern cities comprise the highest fractions in the low and medium severity categories.

Table 1.2: Summary Statistics: City-Level Data by Severity Group

	Low Severity	Medium Severity	High Severity
Mean Severity Index	0.00	0.02	0.20
	(0.00)	(0.01)	(0.16)
Mean Rainfall, 1968 April	2.12	2.43	1.93
	(1.51)	(1.38)	(0.79)
Mean Rainfall, 1967 April	2.86	3.15	2.94
	(2.06)	(1.65)	(1.15)
Mean Total Population, 1975	4818.92	8592.17	34931.93
	(3095.43)	(6600.52)	(46363.62)
Mean US-born population, 1975	4459.24	7942.93	28358.93
	(2892.94)	(6140.56)	(33559.44)
Black Proportion of Population, 1975	0.11	0.25	0.37
	(0.11)	(0.14)	(0.18)
South-born Proportion of Population, 1975	0.32	0.36	0.22
	(0.32)	(0.33)	(0.21)
Percent Moved at All	0.52	0.52	0.45
	(0.15)	(0.14)	(0.15)
Percent Moved between Cities within States	0.20	0.19	0.14
	(0.09)	(0.08)	(0.10)
Percent Moved Within Cities	0.21	0.22	0.22
	(0.07)	(0.06)	(0.09)
Percent Moved between States Within Region	0.05	0.05	0.04
	(0.03)	(0.03)	(0.04)
Percent Moved between Regions	0.06	0.06	0.06
	(0.04)	(0.03)	(0.03)
South	0.38	0.33	0.07
	(0.49)	(0.48)	(0.27)
West	0.33	0.19	0.14
	(0.48)	(0.40)	(0.36)
Midwest	0.17	0.29	0.29
	(0.38)	(0.46)	(0.47)
Northeast	0.12	0.19	0.50
	(0.33)	(0.40)	(0.52)
N	66	42	14

Notes: The sample for the summary statistics is the same as that in city-level 1st stage. Standard deviations are in parenthesis. All movement refer to movement between 1975 and 1980. See the definition of severity index/group and regions in the paper.

1.5.2 First Stage of The 2SLS Estimates

Table 1.3 shows the first-stage results of the 2SLS estimation. Rainfall in April 1968 is a significant predictor of the riot severity index. The dependent variable in the first two columns is the severity index, and that in columns 3 and 4 is the dummy variable representing the three severity groups, taking values 0 to 2 from the low to high severity group. Regardless of how the riot severity is measured, the results show that cities with more rainfall in April 1968 experienced significantly less severe rioting after controlling population, region, and black proportion of the population. This result is consistent with Collins and Margo's (2007) estimation.

A valid instrumental variable should also satisfy the exclusion restriction, which requires that rainfall in April 1968 affects migration outcomes only by influencing the riot severity. Although rainfall is independent in the sense that it is not caused by anything that also determines migration, one may be concerned that rainfall can influence migration in ways other than rioting. For example, much rainfall may cause people to relocate to places with sunnier days, or much rainfall in April may induce seasonal migration. However, as shown in columns 2 and 4 of Table 1.3, the coefficients on rainfall in April 1968 remain significant and negative after controlling the rainfall level in April 1967. In addition, Collins & Margo (2007) included additional information such as annual rainfall data from 1931- 1960, the presence of a city manager, and the change in log median value of all residential properties between 1950 and 1960 in their sample. Using the overlapped observations between their sample and mine (74 cities), I estimate similar first-stage specifications and find that the coefficient on the instrumental variable remains significant and negative. The results are shown in Table A.1 of Appendix A. Once controlling for the rainfall level in April 1968, the average annual rainfall level over the years and the average April rainfall are poor predictors of riot severity.

Table 1.3: First Stage Results

	Severity Index	Severity Index	Severity Group	Severity Group	Riot
Rainfall, April 1968	-0.0100**	-0.0101**	-0.0718**	-0.0785**	-0.0308
	(0.00420)	(0.00481)	(0.0294)	(0.0351)	(0.0291)
Rainfall, April 1967		0.000178		0.0121	
		(0.00319)		(0.0332)	
Percent black	0.230***	0.230***	2.115***	2.113***	1.504***
	(0.0772)	(0.0778)	(0.343)	(0.345)	(0.285)
ln(population)	0.0339**	0.0339**	0.330***	0.333***	0.176***
	(0.0130)	(0.0134)	(0.0461)	(0.0463)	(0.0382)
West	0.0277*	0.0275*	0.153	0.141	0.107
	(0.0147)	(0.0142)	(0.130)	(0.131)	(0.113)
Midwest	0.0413**	0.0411**	0.390***	0.376***	0.252***
	(0.0169)	(0.0177)	(0.102)	(0.113)	(0.0882)
Northeast	0.0350***	0.0348**	0.452***	0.441***	0.222**
	(0.0130)	(0.0142)	(0.128)	(0.136)	(0.106)
N	122	122	122	122	122
F	5.529	4.743	65.46	56.76	24.88

Notes: Robust standard errors are in parenthesis. Sample includes all cities in the triple matched data.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

1.5.3 Different Types of Migrations for All Individuals

The first set of results provides some context and baseline observations on the impact of the 1960s racial riots on general migration patterns between 1975 and 1980. The sample includes all non-schooling 30-50-year-old individuals in matched data, including both US-born and non-US-born populations. Table 1.4 presents the impact of riots on the probability of moving at all for black and white populations separately. The dependent variable is a dummy equal to 1 if the individual is living at least in a different household in 1980 compared to in 1975. Overall, both races have negative estimates, although only the OLS estimate of the white population is statistically significant (-0.156 with clustered robust standard errors of 0.0664). 2SLS estimates are larger in magnitude than OLS estimates. The coefficient on the variable female is negative and significant and that on the variable "has child" is positive and significant. This suggests that women and people without children are less likely to move between 1975 and 1980, holding city population, racial, and birthplace compositions constant. In both OLS and 2SLS estimations, the white population seems to be more likely to move when there is a higher proportion of the black population in the city.

Table 1.4: Probability of Moving at All 1975-1980

	Black		White	
	OLS	2SLS	OLS	2SLS
Index	-0.177	-1.206	-0.156**	-0.586
	(0.178)	(0.969)	(0.0664)	(0.591)
Female	-0.0626***	-0.0626***	-0.0543***	-0.0544***
	(0.00424)	(0.00427)	(0.00210)	(0.00211)
Has child	0.0380***	0.0381***	0.0468***	0.0469***
	(0.00583)	(0.00583)	(0.00638)	(0.00637)
ln(Population)	-0.00377	0.0273	-0.00182	0.0101
	(0.0106)	(0.0330)	(0.00732)	(0.0219)
Percent black	0.0821	0.290	0.266***	0.345**
	(0.0888)	(0.178)	(0.0754)	(0.139)
Percent born in the South	-0.394***	-0.454***	-0.262***	-0.269***
	(0.101)	(0.117)	(0.0849)	(0.0921)
Control for Age	Y	Y	Y	Y
Control for Region	Y	Y	Y	Y
Birth State FEs	Y	Y	Y	Y
N	67905	67905	218016	218016

Notes: Robust standard errors (in parenthesis) are clustered at the city level.
Sample includes non-schooling 30-50-year-old individuals.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 1.5 tabulates the 2SLS results from several different estimations. The first two columns present the entire sample, whereas the following columns indicate subsamples of individuals born in various regions. Each row represents the coefficients from estimations using different dependent variables as listed on the left of the table. For example, the two estimates in the upper left corner are the exact 2SLS estimates shown in Table 1.4, showing the impact of riots on people's probability of moving at all. Although these two estimates are not statistically significant, some of the estimates become significantly negative when breaking down the different types of movement. These measures of movement reflect the distances and, thus, the costs of migration. The costs may include direct monetary costs associated with traveling but also indirect costs of adjusting to a different environment and culture. For example, the black population is less likely to move within their city (-1.337 with standard error 0.664) and move between regions (-0.367 with standard error 0.167) when the city they lived in experienced more severe rioting.

The results can also be considered separately for people born in different regions. Western and midwestern-born blacks are more likely to move within the state, and northeastern-born blacks are less likely to move within the state when they experience more severe rioting. All the statistically significant estimates for whites are negative, regardless of where they were born.

1.5.4 Return Migration for Individuals Stayed outside Birthplace

So far, I've presented the migration patterns for all individuals in the sample, looking at various types of movement. It would be intriguing to zoom in to see the decisions regarding returning to one's origin. Since the census data only provides information on birth states, it is only possible to look at the movement back to the states or regions where people were born. To highlight the return movement, I must exclude individuals who have never moved outside their home states or regions. Therefore, the sample includes people who, in 1975, lived in a state or

Table 1.5: Impact of Riots on Various Movements 1975-1980

	All		Southern-born		Western-born		MidWestern-born		Northeastern-born	
	Black	White	Black	White	Black	White	Black	White	Black	White
Move	-1.206	-0.586	-1.293	-0.101	-0.793	-0.371	-0.351	-1.742*	-3.054*	-0.814
	(0.969)	(0.591)	(1.073)	(0.647)	(2.409)	(0.629)	(1.463)	(0.953)	(1.589)	(1.159)
Move within city	-1.337**	-0.126	-1.207*	-0.00409	-4.338**	0.783	-2.032*	-0.668*	0.283	-0.224
	(0.664)	(0.332)	(0.725)	(0.492)	(2.196)	(0.745)	(1.082)	(0.406)	(1.105)	(0.432)
Move within state	0.0683	0.475	-0.0882	0.857	3.577**	-0.435	2.156***	0.735	-3.650***	1.822
	(0.586)	(0.643)	(0.558)	(0.752)	(1.584)	(1.310)	(0.745)	(0.762)	(1.289)	(1.149)
Move within region	0.429	-1.006***	0.473	-0.656**	0.374	-1.045	-0.249	-1.307***	1.615*	-0.993**
	(0.333)	(0.321)	(0.338)	(0.335)	(1.492)	(1.001)	(0.280)	(0.287)	(0.930)	(0.411)
Move between region	-0.367**	0.0704	-0.471***	-0.298	-0.407	0.326	-0.226	-0.501	-1.302*	-1.420*
	(0.167)	(0.394)	(0.171)	(0.371)	(0.948)	(0.380)	(0.522)	(0.440)	(0.759)	(0.734)
N	67905	218016	42189	48667	1823	30425	8382	51659	11168	53518

Notes: Robust standard errors (in parenthesis) are clustered at the city level.I control for age and age squared, whether have children, gender, city population, fractions of black and southern-born populations. Region indicator and birth states FE are inclueded.
Sample includes non-schooling 30-50-year-old individuals.
* p<0.1, ** p<0.05, *** p<0.01

region that was different from their home state or region.

Tables 1.6 and 1.7 show the results for the subsample of people living outside their home states. The dependent variable in Table 1.6 is a dummy equal to 1 if individuals had moved at all, and that in Table 1.7 is a dummy equal to 1 if they had moved to their birth states. As presented in the table, both black and white individuals are less likely to move back to their home states when there's more severe rioting.

Table 1.6: Outside-home-state Subsample: Probability of Moving at All 1975-1980

	Black		White	
	OLS	2SLS	OLS	2SLS
Index	-0.200	-1.911	-0.151**	-1.024
	(0.210)	(1.352)	(0.0733)	(0.691)
Female	-0.0663***	-0.0666***	-0.0591***	-0.0595***
	(0.00563)	(0.00553)	(0.00274)	(0.00281)
Has child	0.0313***	0.0311***	0.0377***	0.0377***
	(0.00879)	(0.00890)	(0.00530)	(0.00530)
ln(Population)	0.000734	0.0526	0.000582	0.0262
	(0.0141)	(0.0466)	(0.0118)	(0.0277)
Percent black	-0.0861	0.299	0.117**	0.310**
	(0.107)	(0.273)	(0.0472)	(0.157)
Percent born in the South	-0.00583	-0.131	0.0283	-0.0274
	(0.0475)	(0.106)	(0.0346)	(0.0578)
Control for Age	Y	Y	Y	Y
Control for Region	Y	Y	Y	Y
Birth State FEs	Y	Y	Y	Y
N	35154	35154	78424	78424

Notes: Robust standard errors (in parenthesis) are clustered at the city level.
Sample includes US-born non-schooling 30-50-year-old
individuals who in 1975 lived in a different state from their birth state.
* p<0.1, ** p<0.05, *** p<0.01

Table 1.7: Outside-home-state Subsample: Probability of Returning to Home State 1975-1980

	Black		White	
	OLS	2SLS	OLS	2SLS
Index	-0.0169	-0.354*	-0.0416***	-0.435**
	(0.0155)	(0.214)	(0.0139)	(0.217)
Female	-0.00595***	-0.00600***	-0.00917***	-0.00930***
	(0.00175)	(0.00174)	(0.00165)	(0.00164)
Has child	0.00173	0.00170	0.0113***	0.0113***
	(0.00358)	(0.00358)	(0.00288)	(0.00288)
ln(Population)	0.000909	0.0115	-0.00247	0.00991
	(0.00125)	(0.00700)	(0.00229)	(0.00771)
Percent black	-0.00584	0.0782	0.0791***	0.170***
	(0.0151)	(0.0575)	(0.0140)	(0.0534)
Percent born in the South	-0.000874	-0.0246	-0.0178*	-0.0417**
	(0.00951)	(0.0157)	(0.0101)	(0.0160)
Control for Age	Y	Y	Y	Y
Control for Region	Y	Y	Y	Y
Birth State FEs	Y	Y	Y	Y
N	35154	35154	78424	78424

Notes: Robust standard errors (in parenthesis) are clustered at the city level.
Sample includes US-born non-schooling 30-50-year-old
individuals who in 1975 lived in a different state from their birth state.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Tables 1.8 and 1.9 show similar estimations as in Table 1.6 and Table 1.7, but with a subsample of people who lived outside their home regions. Black individuals were less likely to return to their home regions when they experienced more severe rioting. The 2SLS estimates on returning to their home region for white individuals are not statistically significant.

Table 1.8: Outside-home-region Subsample: Probability of Moving at All1975-1980

	Black		White	
	OLS	2SLS	OLS	2SLS
Index	-0.216	-2.746	-0.147*	-1.758**
	(0.209)	(1.922)	(0.0751)	(0.783)
Female	-0.0685***	-0.0688***	-0.0597***	-0.0601***
	(0.00667)	(0.00654)	(0.00348)	(0.00351)
Has child	0.0315***	0.0310***	0.0397***	0.0398***
	(0.00975)	(0.0100)	(0.00632)	(0.00634)
ln(Population)	0.00511	0.0816	0.000388	0.0497
	(0.0146)	(0.0644)	(0.0125)	(0.0306)
Percent black	-0.0619	0.543	0.122**	0.493***
	(0.120)	(0.451)	(0.0577)	(0.177)
Percent born in the South	0.00735	-0.176	0.0237	-0.0670
	(0.0691)	(0.162)	(0.0430)	(0.0652)
Control for Age	Y	Y	Y	Y
Control for Region	Y	Y	Y	Y
Birth State FEs	Y	Y	Y	Y
N	28604	28604	51284	51284

Notes: Robust standard errors (in parenthesis) are clustered at the city level.
Sample includes US-born non-schooling 30-50-year-old
individuals who in 1975 lived in a different region from their birth region.
* p<0.1, ** p<0.05, *** p<0.01

Table 1.9: Outside-home-region Subsample: Probability of Returning to Home Region 1975-1980

	Black		White	
	OLS	2SLS	OLS	2SLS
Index	-0.0243	-0.744**	-0.0434*	-0.849
	(0.0190)	(0.359)	(0.0234)	(0.527)
Female	-0.00914***	-0.00916***	-0.00843***	-0.00852***
	(0.00259)	(0.00258)	(0.00199)	(0.00198)
Has child	0.00300	0.00288	0.0183***	0.0183***
	(0.00389)	(0.00387)	(0.00441)	(0.00441)
ln(Population)	0.00206	0.0247**	-0.00681	0.0192
	(0.00174)	(0.0115)	(0.00412)	(0.0182)
Percent black	-0.0327	0.154	0.0842***	0.275**
	(0.0238)	(0.0993)	(0.0287)	(0.129)
Percent born in the South	0.0145	-0.0341	-0.0107	-0.0549*
	(0.0231)	(0.0341)	(0.0176)	(0.0322)
Control for Age	Y	Y	Y	Y
Control for Region	Y	Y	Y	Y
Birth State FEs	Y	Y	Y	Y
N	28604	28604	51284	51284

Notes: Robust standard errors (in parenthesis) are clustered at the city level.
Sample includes US-born non-schooling 30-50-year-old
individuals who in 1975 lived in a different region from their birth region.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 1.10 presents the results of the conditional movement. In each row, I'm including a subsample of individuals who have moved, moved to other states, and moved to other regions. The estimates show the impact of riots on the probability of moving to the home state conditioning on the fact that they have moved somewhere. For example, conditioning on moving to other states, black individuals are less likely to move to their home states, while white individuals are more likely to move to their home states when they experience more severe rioting.

Table 1.10: Outside-home-state Subsample: Impact of Riots on Conditional Movement 1975- 1980

	Black	White
Move home conditional on moving at all	-0.520	-0.495*
	(0.337)	(0.291)
Move home conditional on moving to other states	-2.084	0.254
	(1.660)	(0.356)
Move Home conditional on moving to other regions	-0.400	1.301**
	(1.222)	(0.539)
N	1883	9835

Notes: Robust standard errors (in parenthesis) are clustered at the city level.
I control for age and age squared, whether have children, and gender.
level. I also control for city population, fractions of black and southern-born populations.
Region indicator and birth states FE are inclueded. Sample includes US-born non-schooling 30-50-year-old individuals who in 1975 lived in a different state from their birth state.
* p<0.1, ** p<0.05, *** p<0.01

1.5.5 Return Migration for the Great Migration Migrant

After gaining some insights into the migration patterns in the previous set-ups, I now show the impact of the riots on the migration decisions of people who participated in the Great Migration. Table 1.11 shows the OLS and 2SLS estimates for the probability of moving at all for non-schooling 30-50-year-old individuals who were born in the South and lived in the North in 1975. For the black population, the riot severity index does not seem to affect the probability of moving to any place at a significant level. The white population is less likely to move somewhere when experiencing more severe riots. In Table 1.12, we see that the instrumental variable is starting to pick up some significantly negative impact of riot severity on both black and white people's decision to move to the South between 1975 and 1980.

Table 1.11: Migrant Subsample: Probability of Moving at All 1975-1980

	Black		White	
	OLS	2SLS	OLS	2SLS
Index	-0.216	-2.550	-0.259*	-3.784**
	(0.210)	(2.237)	(0.142)	(1.792)
Female	-0.0651***	-0.0653***	-0.0507***	-0.0509***
	(0.00695)	(0.00684)	(0.00779)	(0.00779)
Has child	0.0360***	0.0355***	0.0384***	0.0387***
	(0.0110)	(0.0112)	(0.00980)	(0.00998)
ln(Population)	0.00159	0.0717	0.0237	0.138**
	(0.0131)	(0.0764)	(0.0192)	(0.0662)
Percent black	0.0825	0.656	0.0948	0.723*
	(0.314)	(0.573)	(0.193)	(0.411)
Percent born in the South	-0.340	-0.560	0.275	0.727*
	(0.812)	(0.993)	(0.438)	(0.432)
Control for Age	Y	Y	Y	Y
Control for Region	Y	Y	Y	Y
Birth State FEs	Y	Y	Y	Y
N	26098	26098	12250	12250

Notes: Robust standard errors (in parenthesis) are clustered at the city level.
Sample includes non-schooling 30-50-year-old individuals
who were born in the South and lived in the North in 1975.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 1.12: Migrant Subsample: Probability of Returning to the South 1975-1980

	Black		White	
	OLS	2SLS	OLS	2SLS
Index	-0.0316	-1.038***	-0.0640	-2.690*
	(0.0190)	(0.367)	(0.0505)	(1.583)
Female	-0.00817***	-0.00815***	-0.0135***	-0.0133***
	(0.00272)	(0.00271)	(0.00490)	(0.00490)
Has child	0.00632	0.00617	0.0121	0.0120
	(0.00432)	(0.00430)	(0.00750)	(0.00754)
ln(Population)	0.00496***	0.0373***	0.000414	0.0897
	(0.00179)	(0.0122)	(0.00716)	(0.0542)
Percent black	-0.0959**	0.148	-0.0523	0.485
	(0.0475)	(0.0993)	(0.150)	(0.376)
Percent born in the South	0.201*	0.183	0.314	0.587*
	(0.115)	(0.113)	(0.348)	(0.307)
Control for Age	Y	Y	Y	Y
Control for Region	Y	Y	Y	Y
Birth State FEs	Y	Y	Y	Y
N	26098	26098	12250	12250

Notes: Robust standard errors (in parenthesis) are clustered at the city level.
Sample includes non-schooling 30-50-year-old individuals
who were born in the South and lived in the North in 1975.
* p<0.1, ** p<0.05, *** p<0.01

Table 1.13 shows 2SLS estimates of the riot severity coefficient for the southern-born and northern-born black and white population, similar to Table 1.5. Northern-born white individuals who were in northern cities with more severe rioting were more likely to move to other cities in the same states but less likely to move to other states within the region and to the South. This could mean that severe riots in the city made them prefer to leave the city and, at the same time, avoid going to places in a different region and the South where there used to be much racial unrest. A similar avoidance pattern is also seen in southern-born white people. Southern-born whites in cities with more severe rioting were less likely to move to other states and return to the South. Interestingly, we see that southern-born black individuals in cities with more severe rioting were less likely to go to the South. The economic damage caused by the riots may constrain their ability to move far.

Table 1.13: Migrant Subsample: Impact of Riots on Various Movements

	Southern-born		Northern-born	
	Black	White	Black	White
Move	-2.550	-3.784**	-1.149	-1.511
	(2.237)	(1.792)	(1.294)	(1.015)
Move within city	-2.081	0.0621	-2.319**	-0.542
	(1.465)	(0.947)	(1.003)	(0.615)
Move within state	0.999	0.655	1.536*	1.178
	(1.200)	(1.853)	(0.801)	(1.165)
Move within region	-0.453	-1.652**	-0.166	-1.473***
	(0.507)	(0.761)	(0.457)	(0.536)
Move between region	-1.016**	-2.849	-0.200	-0.673
	(0.448)	(1.771)	(0.476)	(0.611)
Move to the South	-1.038***	-2.690*	-0.109	-0.564*
	(0.367)	(1.583)	(0.221)	(0.323)
N	26098	12250	24795	151133

Notes: Robust standard errors (in parenthesis) are clustered at the city level.
I control for age and age squared, whether have children, and gender
I also control for city population, fractions of black and southern-born populations. Region indicator and birth states FE are inclueded.
Sample includes non-schooling 30-50-year-old individuals who lived in the North in 1975.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 1.14 presents the impact of riots on conditional movement. For all samples, riot severity has negative impacts on people's decision to move to the South conditional on moving at all and moving to other states and other regions. The conditional movement to the South reveals more about people's preferences than financial abilities. The dire consequences of racial riots and the high-level racial tension in the cities may discourage them from going to the South, where used to be many racial riots. Southern-born blacks and whites may be reminded of the racial tension they used to have in the South by the present riots.

Table 1.14: Migrant Sub-sample: Impact of Riots on Conditional Movement

	Southern-born		Northern-born	
	Black	White	Black	White
Move to the South conditional on moving at all	-1.988***	-3.170*	-0.182	-0.919*
	(0.655)	(1.914)	(0.433)	(0.497)
Move to the South conditional on moving to other states	-2.179	-1.354	-2.202	-0.792
	(3.019)	(1.392)	(2.067)	(1.014)
Move to the South conditional on moving to other regions	-3.492**	-1.947	-4.933**	-3.805***
	(1.532)	(1.310)	(2.158)	(1.142)
N	1330	2025	879	9456

Notes: Robust standard errors (in parenthesis) are clustered at the city level.
I control for age and age squared, whether have children, gender, city population, and fractions of black and southern-born populations. Region indicator and birth states FE are included. Sample includes non-schooling 30-50-year-old individuals who lived in the North in 1975.
* p<0.1, ** p<0.05, *** p<0.01

In all of the specifications, I control for the rainfall in April 1976 and the annual average rainfall for the cities. This is to drive out the variations in migration due to seasonal reasons and geographic preferences that are purely based on weather conditions. One caveat of the results is that they only capture the impact of the 1960s racial riots on migration decisions between 1975 and 1980, not right after the riots. Hence it is better to treat the results as estimates for long-run impact. Also, people who wish to move to the South may have already migrated by 1975 and hence the results capture the movement of people who did not leave immediately after the riots. In addition, the measure of migration is not perfect. People who are observed in the same place in 1975 and 1980 may have moved during this period.

1.6 CONCLUSION

Using Carter's (1989) comprehensive data on racial riots from 1964 to 1971 and the 1980 US Census data, I study the impact of the 1960s racial riots on migration decisions between 1975 to 1980. Following Collins and Margo (2007), I use rainfall in April 1968 as an instrumental variable to estimate the causal impact. I show that higher riots severity in the 1960s racial riots leads to a lower probability of return migration for southern-born migrants, even conditional on moving to other states. This pattern is also true for northern-born blacks and whites. In addition, northern-born white individuals in cities experiencing more severe riots were more likely to move to other cities in their states. These results enrich the Great Migration literature by investigating the reason for the return movement in the 1970s through rigorous economic analysis. This paper also sheds light on the impact of racial riots on people's migration decisions.

While this paper does not provide direct empirical evidence for the mechanism of the impact, the results suggest some possible explanations. The economic damage caused by the riots may constrain their ability to move far since riot severity reduces peoples' probability of both moving to other states and to the South. The riots may also remind people of the racial tension and avoid going to the South, which used to have intense persecution of blacks. Future work could include an investigation of these possible mechanisms. In particular, we could find economic variables to directly test whether return migration or the lack of it is driven by economic reasons. Incorporating measures of city-to-city migration distance also will provide more insights into people's preferences regarding migration decisions. Also, it is worthwhile exploring systematic factors that affect people's decision to return to the South, such as changing economic and social conditions.

CHAPTER 2

The Impact of Retractions on Scholarly Production

2.1 INTRODUCTION

Academic honesty and reliable scientific results are pivotal in scholarly production and the intellectual progress of societies. Unfortunately, the scholarly community sometimes confronts problems of "false science". At best, false science arises from unintentional mistakes resulting in unreliable findings, but at worst, it can involve outright falsification and fabrication of data and results, plagiarism, unethical research conduct, and copyright infringement. In a meta-analysis of 18 studies investigating the prevalence of scientific malpractices published between 1988 and 2005, Fanelli (2009) found an average of "1.97% of scientists admitted to having fabricated, falsified or modified data or results at least once" and "up to 33.7 % admitted other questionable research practices". The numbers are even higher in surveys on people's knowledge of their colleagues' misconduct, with admission rates of 14.12% for falsification and 72% for other questionable research practices (Fanelli, 2009). Using estimation methods from the genomics community and P-values collected from over 77 thousand papers published in medical journals between 2000 and 2010, Jager & Leek (2014) estimated that "the overall rate of false science among reported results is 14%". Screening over 20 thousand papers published in 40 scientific journals from 1995 to 2014, Bik et al. (2016) found that 3.8% of them contained problematic figures, with at least half showing traits of deliberate image manipulation. The problem of false science is also present in fields other than hard sciences. Using survey results from the 1998 American Economic Association meeting, List et al. (2007) found that more than 4% of economists surveyed admitted to having falsified data in research.

False science could have large detrimental impacts on both the scholarly community and the world beyond academia. Fraudulent scientific studies are costly to funding sources (Edwards & Roy, 2017). Tracking approximately 150 US articles published between 1992 and 2012 that were retracted due to misconduct, such as data falsification or fabrication, Stern et al. (2014) reported that these papers accounted for about $58 million in direct funding by NIH, with a mean of $392,582. This figure does not include further wasted resources and time associated with follow-up studies. Analyzing articles that belong to the same intellectual space as the retracted papers, Azoulay et al. (2015) found fewer new articles and funding flows into these fields after retraction. False science could also damage the well-being of the public. In 1998, a study published in *Lancet* suggested a link between the measles, mumps, and rubella (MMR) vaccine and autism in children. It was later found to be fraudulent and retracted in 2010. However, wide publicity of the findings has led to dropping vaccination rates in the UK and the US, causing subsequent measles outbreaks worldwide (Deer, 2010, 2011b,c,a; Rao & Andrade, 2011).

Many disciplines have used retractions as mechanisms to inform the scientific community about the mistakes and misconduct in published works. Understanding the drivers and impact of reactions will reveal the efficiency of knowledge governance and generate useful policy recommendations. A few studies have investigated the outcomes of retraction, mostly focusing on the biomedical sciences (Furman et al., 2012; Lu et al., 2013; Azoulay et al., 2015, 2017; Jin et al., 2019; Albrese, 2022). We know relatively less about the drivers and impact of retractions across different fields and the reasons behind retraction.

Using a unique dataset of retracted papers collected by Retraction Watch and various econometric models, I investigate the factors associated with the time to retraction and reasons for retraction. I find that the number of authors positively correlates with time-to-retraction, possibly due to increased communication costs when having more authors. Papers with at least one author that is affiliated with a US institution have a longer time to retract and are more likely to be revealed with clear reasons for retractions. The number of fields is negatively correlated with time-to-retraction, while the number of subjects is positively correlated with it. Compared to papers in social sciences, papers in environmental sciences and business and technology take less time to retract, while papers in humanities take longer to retract. Papers in environmental sciences and business and technology are less likely to be retracted for bad or ugly reasons instead of uncertain reasons, while papers in health sciences are more likely to be retracted for good reasons instead of uncertain reasons, compared to papers in social sciences. Having at least one author who is affiliated with a hospital also increases the probability of having a clearly stated reason for retraction, although the effect becomes insignificant after controlling for fields. Interestingly, having at least one author who is affiliated with a university decreases the probability of having a clearly stated reason for retraction. In addition, the publication year is negatively correlated with time-to-retraction, suggesting that either the speed of discovering false science or the speed of responding to mistakes in papers (or both) has increased over the years. It is also evident that there has been improvement in clearly stating retraction reasons over the years.

Following Furman et al. (2012), I use the nearest neighbor articles published in the same issue and journal where the retracted paper appears as the control group to set up a Difference-in-Difference (DID) model. Using the DID framework, I provide plausible causal evidence on the impact of retractions on annual citation counts. I find that retraction decreases the annual citations received by papers, and the impact is greater for papers that are retracted due to severe misconduct than those with milder mistakes.

The rest of the paper is organized as follows. Section 2 provides background information and a review of related literature on false science and retraction. Section 3 introduces the datasets I use for my analysis. Section 4 specifies in detail the empirical models I employ. Section 5 presents the results of my analysis. Section 6 provides some additional discussions on the results, and Section 7 concludes the paper.

2.2 BACKGROUND AND RELATED LITERATURE

Retractions are important mechanisms for maintaining the integrity and quality of scientific literature, and they should be discussed in the greater context of knowledge governance. Understanding the process of discovering false science and retracting problematic works provide important guidance in interpreting the empirical findings of the study.

2.2.1 The Discovery of False Science

It is not difficult to see the damages caused by false science once it is uncovered, but we know relatively less about how efficient we are in policing false science. Science and academia are often expected to self-correct; however, discovering and disclosing false science is time-consuming and complicated. Discoveries of false science can take place in many ways. Some mistakes in published works are found when subsequent researchers fail to replicate the original results. For example, in 2014, a group of England neuroscientists voluntarily retracted one of the published papers after their graduate student found a fatal error in their study when she was trying to replicate part of their results (De Haas et al., 2020; Marcus, 2020). Measuring and disclosing reproducibility has affected the fate of many papers, and sometimes an entire field of study. In the 2010s, a group of studies failed to replicate a highly controversial paper by Cornell psychologist Daryl J. Bem, who in the paper claimed to find evidence that unanticipated future events have anomalous retroactive influences on one's current responses (Bem, 2011). Meanwhile, there have also been broader discussions about replication failures in psychology. In 2015, *Science* published results from the Reproducibility Project, in which 100 experiments published in 2008 in three top psychology journals were replicated. They found that only 36 percent of the replications have significant results (Open Science Collaboration, 2015). The replication crisis in the 2010s has led to growing attention on methodological issues and research practices in psychology, and reforms such as result-blind peer review, pre-registration of studies, and metadata tools for tracking replications (Schimmack, 2020).

Some problems are discovered when readers and audiences find suspicious results and information in the published works. For instance, in 2020, a group of scientists in Egypt claimed that they had shown that incorporating a cheap diabetes drug (Metformin) would double the efficacy in treating moderate to severe depression (Abdallah et al., 2020). The remarkable results attracted the attention of Eric Ross, who was then a psychiatry resident at Massachusetts General Hospital then (now an assistant professor of psychiatry at the University of Vermont), when he was listening to a report about the study in a popular psychiatry podcast. Yet he later found that the statistics presented in this study and another study by the same authors seem too good to be true and glaringly similar to the numbers in a different clinical trial (Joelving, 2023). He shared his suspicions with the publishing journals, *Neurotherapeutics* and *CNS Neuroscience & Therapeutics*. *Neurotherapeutics* retracted the Metformin paper in September 2022, and *CNS Neuroscience & Therapeutics* has initiated an investigation regarding the second paper (Abdallah et al., 2022; Joelving, 2023).

People communicate their concerns about published works differently. Some contact authors and editors privately, some leave anonymous comments on public platforms, and some report it to authorities. Over the years, a few platforms have been established for concerned readers and whistleblowers to discuss their suspicions with others. One example is PubPeer founded by neuroscientist Brandon Stell (Couzin-Frankel, 2015). It gained its reputation after an anonymous post pointed out image duplications in a high-profile paper published in *Cell*, which then issued an erratum (Couzin-Frankel, 2013). The website now attracts many scholars to post comments regarding published papers anonymously, after which the authors of the commented papers will be notified and invited to reply. The discussions have prompted numerous corrections and retractions of published works (Couzin-Frankel, 2015). Similar venues that existed but were discontinued include science-fraud.org, and PubMed Commons[1].

2.2.2 The Scope and Process of Retractions

When concerns about published works are raised either directly to journals and authors, or indirectly through social media or public platforms, actions need to be

[1] Although PubMed Commons was discontinued due to low usage, the comments are still available for download at https://ftp.ncbi.nlm.nih.gov/pubmed/pubmedcommons/.

taken at different levels. While there is no universal standard for handling these concerns, the Committee on Publication Ethics (COPE) has created general guidelines now followed by many journals. According to COPE, journal editors should contact authors for responses, and follow a series of steps to evaluate the validity of the issue (COPE Council, 2015b,a). Depending on the nature of the problems raised, editors could choose to publish a retraction, a correction, or an expression of concern. Unlike corrections or expressions of concern, which are often issued when there're minor errors or unproven problems in papers, retractions are used for papers with major mistakes, duplications, or confirmed academic misconduct and ethical issues. According to COPE's Retraction Guidelines, for each retracted paper, a freely accessible notice of retraction should be issued and linked to all versions of the papers, stipulating the reason for the retraction and the party that initiated the retraction (COPE Council, 2019). Only in extreme cases, the retracted papers can be removed from online publication (COPE Council, 2019).

The actual retraction practice varies widely across different journals and fields. Although editors are expected to "negotiate with authors and attempt to agree on a form of wording that is clear and informative to readers and acceptable to all parties" (COPE Council, 2019), many find that some retraction notices do not adequately reveal the misconduct involved (Brainard et al., 2018). Some studies have investigated the process of retraction in biomedical sciences. Decullier et al. (2013) retrieved all Medline articles retracted in 2008 and their corresponding retraction notices and identified reasons and clear signs for retraction. They found that 22% of the retracted articles have no mention of retraction in the original publication. Elia et al. (2014) evaluated 88 papers that warranted retraction due to the lack of ethical approvals in Germany and found that the guidelines for retracting articles are incompletely executed. In addition, the retraction process could take a long time due to lengthy communications between editors, authors, and institutions. As pointed out by H. Holden Thorp, the editor-in-chief of *Science* journals, when editors receive a report of problems in a published paper, authors deny academic misconduct most of the time. Editors then need to contact the author's institutions, which often give inconclusive answers that journals need to follow up with every 3 to 6 months. Institutions often take a long time to reach conclusions as they are burdened with legalistic regulations for investigating academic misconduct and possible disputes or legal threats from unhappy authors against institutions (Thorp, 2022).

A few studies have investigated the trends and influence factors of retractions quantitatively. Using data from the PubMed database and Web of Science, Furman et al. (2012) investigated the factors correlating with the probability of retractions and time-to-retractions. They found that retractions happen more frequently among highly cited articles. They also found that the average retraction time is less than two years and is uncorrelated with the authors' prominence (Furman et al., 2012). Using data from Retraction Watch, Brainard et al. (2018) documented that the absolute number of annual retractions has increased at a decreasing rate, and much of the increase in retractions reflects improved oversight of journals. In addition, some scholars have studied the characteristics of retracted papers and their authors and journals. Using PubMed papers published from 2008 to 2012, Amos (2014) explored national differences in reasons for retraction. He found that the US retracted the most papers, and China retracted papers mostly for plagiarism and duplicate publication. In addition, rates of plagiarism and duplicate publication were highest in Italy and Finland, respectively. Analyzing journals in PubMed, Fang & Casadevall (2011) found that the frequency of retraction positively correlates with the journal's impact factor. Stern et al. (2014) investigated 2,047 retracted papers in PubMed and found that the time-to-retract has decreased, and the proportion of retractions by authors with a single retraction has increased, indicating a lower barrier to publishing and retracting flawed works.

My study provides new insights into the retraction process by investigating factors associated with time-to-retraction, retraction reason salience, and degree of misconduct using a large dataset. In addition, I also provide evidence of the differences across different fields of study, which is rare in pervious studies.

2.2.3 Impact of Retractions

Several studies have investigated the outcomes of retraction. Furman et al. (2012) analyzed biomedical articles retracted between 1972-2006 and compared them with a matched control sample. They find that retraction causes immediate and long-term declines in follow-on citations. Lu et al. (2013) also used retracted biomedical papers and found that retraction decreases citation counts of prior non-retracted publications by the same authors. This effect is also observed in the prior publications of the authors' citation network by up to four degrees of separation from the retracted paper. In a separate paper, they found that within a collaboration, less eminent authors experience greater citation penalties than the more eminent authors in the team (Jin et al., 2019). Comparing authors' eminence across publications, Azoulay et al. (2017), however, found that more eminent authors are more harshly penalized in cases of fraud or misconduct. Moreover, examing 1,100 biomedical articles and their related subfields, Azoulay et al. (2015) found that the follow-on citations for non-retracted articles in the same intellectual space also decrease following a retraction event. They also find that the arrival rate of new articles and funding flows into these subfields declines after a retraction event.

Almost all studies that investigate the impact of retraction focus on papers in biomedical science with relatively small samples. My study fills in the gap in the literature by providing evidence in other subject areas and conducting across-subject comparisons. In addition, with a larger sample size and richer information about the reasons for retraction, I explore the heterogeneity in the effects to a greater extent.

2.3 DATA

2.3.1 Retraction Data

To investigate the impact of retraction events on citation patterns, I must first identify a reasonable number of scholarly articles that have been retracted. Such information is not as straightforward as it may seem, as many papers are retracted with not-so-obvious indications of retraction. Previously, authors studying the topic of retractions mainly used two sources of data: the PubMed database and Scorpus, which have good coverage of papers in the bio-medical fields with information on retraction. In my study, I use a unique dataset of retracted papers collected by a non-profit organization named Retraction Watch [2]. Retraction Watch was launched in 2010 by Adam Marcus and Ivan Oransky, two longtime health journalists who wanted to know more about the withdrawal process of scientific journals. Over the years, their team collected retracted papers across many journals, disciplines, and countries, investigated the stories behind them, and established a searchable

[2] More information about the organization and their database can be found at: https://retractionwatch.com.

database of retracted papers. Their collection now covers more than 30,000 retracted papers and is considered the largest and most comprehensive of its kind (Brainard et al., 2018). The data includes retracted papers' metadata, including titles, DOI, subjects, fields, article types, journals, publishers, authors, and authors' institutions and countries. It also contains dates of publication and retraction, and reasons for retraction. The entire raw dataset covers papers published between 1923 and 2021 and retracted between 1927 and 2021.

To identify the reasons for retractions, the Retraction Watch team actively looks for additional information beyond the retraction notices published in journals and reports the investigative stories on their website. The team manually noted the specific reasons for retraction using the taxonomy they developed. There are over 100 reasons used in their database, ranging from minor errors like "false affiliation" of authors when publishing the paper, to serious misconduct like "falsification/-fabrication of data". To compare the retraction and citation patterns across different levels of misconduct, I group these papers into four categories, namely the good, the bad, the ugly, and the uncertain. Specifically, the good category includes papers retracted for miscommunications, wrongdoings of third parties, or temporary removals. The bad category comprises papers retracted for honest mistakes in data or results or plagiarism. The ugly category is reserved for papers retracted for more serious misconduct, such as ethical violations, falsification of data or results, and paper mills. The uncertain category is for papers retracted for unknown reasons. A detailed grouping of the reasons is shown in Table B.1 of Appendix B. About two-thirds of the retracted papers in the dataset have more than one reason for retractions. For these papers, I assign their categories to be the worst categories that their reasons belong to. For example, if a paper has an uncertain reason, a good reason, and an ugly reason, it is grouped into the ugly category.

The data also contains information on fields and subjects. Fields refer to broad categories of disciplines, which include social sciences, basic life sciences, health sciences, physical sciences, business and technology, environmental sciences, and humanities. There are also more detailed labels for subjects within each discipline. For example, basic life sciences include subjects like biology-cellular, biology-cancer, anatomy/physiology, biochemistry, and plant biology/botany. Social sciences include subjects like sociology, psychology, political science, and education. Papers in economics are labeled under business and technology.

2.3.2 Control Sample Data

To measure the impact of retractions, I need a set of comparable non-retracted papers for comparison. I follow an empirical approach that has been used by a few economists studying similar questions in their papers (Furman et al., 2012; Azoulay et al., 2015), which I will describe in detail in the next section. In a nutshell, I manually searched and collected the nearest neighbor articles published in the same issue and journal in which the retracted papers appeared. If a paper is the first or the last research paper in the issue, then only one neighbor article is included. If the neighbor article is also retracted, the next nearest un-retracted article is used instead.

2.3.3 Citation Data

To measure the impact of retractions on citations, I need the total and annual citation count received by both the retracted papers and their control groups after they were published. I collect citation information from two sources. The first source is a website named Scite.ai, which provides a comprehensive list of citing academic papers for each referenced paper. I manually searched and downloaded lists, which included the metadata of the citing papers, such as the titles, journals, years, and authors. The second source for citation is Google Scholar, which provides citation counts and links of citing papers to the referenced papers. I scraped Google Scholar for the retracted and control papers' citing papers. Unlike Scite.ai, which only includes academic journal articles with trackable DOIs, Google Scholar links any works that cite the referenced papers including academic journal articles, reports from other countries, and materials for non-academic usage. I use the citation dataset from Scite.ai in my main analysis and use the data from Google Scholar in my robustness checks.

I use the year the citing papers were published as the citation year for the referenced papers. I then clean and organize the data to create a panel of annual citation counts. If there are missing post-publication years in the collection of citing papers, I impute zeros to those years as if there is no citation received in those years. This assumes that the citation data are comprehensive, which I have confirmed by private communications with the Scite.ai staff.

In the base sample, I include papers that were retracted in and before 2015 and were retracted at least 1 year after publication. This gives me enough pre- and post-retraction periods to observe the citation patterns before and after retractions. I also narrowed the sample to papers with at least one of the authors affiliated with a US institution. I exclude papers not found in Scite.ai or Google Scholar and those with zero citations until 2022.

2.4 EMPIRICAL STRATEGY

2.4.1 Factors Affecting Time-to-retraction

To investigate the determinants of time-to-retraction, I use the entire dataset of retraced papers after dropping a few retracted works that are non-academic in nature. I estimate the following baseline specification:

$$TimeToRetract_{ij} = \alpha + \Gamma X_i + \epsilon_{ij} \tag{2.1}$$

where $TimeToRetract_{ij}$ is the number of months (in whole numbers) for each paper i in journal j to retract after publication. X_i is a vector of paper-level covariates, including the number of authors, the number of fields, the number of subjects that the paper is associated with according to the categorization by Retraction Watch, the number of countries in which the authors' affiliated institutions belong, and the year of publication. I also include indicators for the type of institutions with which the authors are affiliated, such as universities and hospitals[3]. In addition, for papers listed under a single field, I also include indicators for the fields of the retracted papers. Since the dependent variable is a count variable and highly skewed with a large number of small values, I estimate the specification through a negative binomial model. Since journal policies and editors' actions are important to the process of retraction, I cluster robust standard errors at the journal level to account for correlations in retraction speed within journals.

The time-to-retraction is a sum of two periods, the time taken for the authors or whistle-blowers to discover the mistakes in papers and the time taken for journals, authors, and institutions to react and execute retractions. Even though it is

[3] I code the institutions to be a university if the names of the institution contain "University", "College", "Institute", "School", "Academy".

difficult to distinguish these two periods separately in my data, some variables provide suggestive evidence for each period. For example, the number of authors and countries may be positively correlated with time-to-retraction, particularly the time taken to react to raised concerns, as the involvement of more parties will increase the cost of communications and investigations. This is especially true if journals and institutions need to seek the authors' consent when initiating retractions. In addition, the number of subjects may be positively correlated with time-to-retraction because it may require more knowledge and time for readers to discover mistakes when the papers cover more subject areas. It is also interesting to see how time-to-retraction differs across countries, subjects, and institutional types.

2.4.2 Factors Affecting The Disclosure and The Degree of Misconduct

The rich information on reasons for retractions in the datasets allows me to examine the factors predisposing papers to have different levels of disclosure and different degrees of misconduct. As described in the data section, I grouped the reasons for retractions into four categories: the good, the bad, the ugly, and the uncertain. I first investigate the factors affecting the probability of having some clearly disclosed reasons for retractions. I group the good, bad, and ugly categories into a single group. I estimate the following model:

$$D_{ij} = \alpha + \Gamma X_i + \epsilon_{ij} \tag{2.2}$$

where D_{ij} is an indicator of retracted paper i from journal j having a revealed reason for retraction. X_i is a vector of paper-level covariates as described in equation 2.1. The sample only includes retracted papers.

In addition, I use a multinomial logit (MNL) model to investigate the determinates affecting the probability that a retracted paper falls into different categories of reason types. The sample includes all the retracted academic papers with clear reasons for retractions. In the analysis, the dependent variable is a discrete variable that takes three unordered and independent reason types: good ($r = 1$), bad ($r = 2$), and ugly ($r = 3$). The probability that paper i belongs to any of the reason types r is conditional on a set of P paper-level variables (x_i) and is represented by the following equation:

$$\pi_r(x_i) = P(y = r|x_i) = \frac{\exp(x_i\beta_r)}{1 + \sum_{k=1}^{3} \exp(x_i\beta_k)} \tag{2.3}$$

for

$$r = 2, 3$$

and

$$\pi_1(x_i) = P(y = 1|x_i) = \frac{1}{1 + \sum_{k=1}^{3} \exp(x_i\beta_k)} \tag{2.4}$$

I use the good reason type ($r = 1$) as the base category and estimate the following specifications:

$$\log[\frac{\pi_r(x_i)}{\pi_1(x_i)}] = \beta_0 + \beta_{1r}x_{1i} + \beta_{2r}x_{2i} + ... + \beta_{Pr}x_{Pi} \tag{2.5}$$

where

$$r = 2, 3$$

The parameters of interest β_{pr} are estimated by the method of maximum likelihood. The independent variables used are similar to those in equation 2.1. A successful MNL model needs satisfaction of the Independence of Irrelevant Alternatives (IIA) assumption, which requires that the odds ratio between any two choices be independent of other available choices. It is arguably convincing that this assumption holds as retracted papers are grouped into these four categories based on the nature of the authors' misconduct, which is independent of my definition of categorization.

2.4.3 Impact of Retractions on Citation Counts

I use a standard difference-in-difference framework to investigate the impact of retraction on the citation count of the retracted papers. Specifically, I use the following baseline specification:

$$\mathbb{E}[y_{ict}|X_{ict}] = exp[\alpha + \beta PostRetraction_{ict} + \mu_i + \lambda_t + \gamma_i + \epsilon_{it}] \tag{2.6}$$

where y_{ict} is the annual citation count received by retracted paper i in year t. $PostRetraction_{ict}$ is a dummy variable that is equal to 1 after retraction, and 0 before retraction or if never retracted. μ_i, λ_t, γ_i are paper, year, and paper's age fixed effects. Robust standard errors are clustered at the retraction case level c (the groups of retracted papers and their corresponding control papers). The fixed effects control for many time-invariant characteristics that could affect citations, such as journal prestige.

Since the dependent variable citation count is extremely skewed with a large number of zeros, I follow the long-time tradition in citation studies to estimate the coefficient via Poisson Pseudomaximum likelihood (PPML) model developed by Correia et al. (2020). The estimates of the coefficients are consistent as long as the mean of the dependent variable is correctly specified (Gourieroux et al., 1984). Such methods have been implemented in many works studying citation counts in a DID framework (Furman et al., 2012; Azoulay et al., 2015; Alabrese, 2022).

The identification of this model requires a well-chosen control group. Ideally, the perfect control group would be papers that are at risk of retraction but never retracted. This means that these papers are problematic, but their problems have not been discovered or treated. However, it is impossible to identify them as we only observe confirmed faulty papers after they are retracted. Following Furman et al. (2012), my control group consists of the nearest neighbor articles published in the same issue and journal in which the retracted paper appears. The identification of causal effects relies on the random nature of the treatment. Choosing articles that happen to be the neighbors of the retracted papers generates a random selection of articles that are very similar to the retracted papers to readers' eyes before the retraction. This minimizes observable variation between the retracted and control papers to the greatest possible degree, controlling implicitly for factors associated with the behavior, quality, and prestige of journals. Although these papers may differ fundamentally from the retracted papers by the quality or integrity of their works, they appear to be similar to retracted papers before retractions take place. Since the goal of the investigation is to study the impact of retraction, the inability to identify problematic papers by both the econometrician and the authors of the follow-on citations makes the control group a reasonable choice. This approach has also been used by a few economists in their study of retraction (Furman et al., 2012; Lu et al., 2013; Azoulay et al., 2017; Jin et al., 2019)). Furthermore, since the retracted papers and control papers are published in the same journal at the same time, there may be spillover effects of citation changes after retractions. If this is true, then it is reasonable to believe that the estimate I obtain by using this method provides a lower bound of the actual impact. Additionally, I will characterize heterogeneity by reasons of retraction, authors' affiliation, characteristics of citing papers, journals, and retraction process.

2.4.4 Event Study of Retraction

To investigate the dynamic effects of retractions over time, I estimated the following equations as proposed by Freyaldenhoven et al. (2021) :

$$Y_{it} = \sum_{k=G-L_G}^{M+L_{M-1}} \delta_k \Delta\zeta_{i,t-k} + \delta_{M+L_M}\zeta_{i,t-M-L_M} + \delta_{-G-L_G-1}(1-\zeta_{i,t+G+L_G}) + \mu_i + \lambda_t + \gamma_i + X'_{it}\Gamma + \epsilon_{it} \tag{2.7}$$

where $\Delta$is the first difference operator, and other notations follow those in equation 2.6. In the case of retraction, the dynamic effects follow a staggered adoption. $\Delta\zeta_{i,t-k}$ is an indicator variable equal to 1 if paper i is retracted exactly k years before year t, $\zeta_{i,t-M-L_M}$ is an indicator variable equal to 1 if paper $i$is retracted at least $M + L_M$ years before year t, and $(1 - \zeta_{i,t+G+L_G})$ is an indicator variable equal to 1 if paper i will be retracted more than $G + L_G$ years after year t. The parameters of interest $\{\delta_k\}_{k=-G-L_G-1}^{k=M+L_M}$ represent the cumulative effects of retraction at different horizons k, and are shown in the event-study plots.

2.5 RESULTS

2.5.1 Descriptive Statistics

In the original data collected and shared by Retraction Watch, there are 30,950 retracted papers with publication years ranging from 1756 to 2021, and retraction years ranging from 1756 to 2011. For my main analysis, I exclude 46 papers that were published before 1980 because there were too few observations in earlier years. Table 2.1 shows the summary statistics for the raw data, which includes 30,904 retracted papers. On average, it took 26.1 months to retract a paper in this sample after publication. There are significant variations in time-to-retraction, with the longest being 412 months and the minimum being 0 months (being published and retracted in the same month). About 16%, 29%, 30%, and 25% of the papers were retracted due to good, bad, ugly, and uncertain reasons, respectively. The number of authors ranges from 1 to 81, with a mean of 3.81, and the number of countries that the authors are affiliated with ranges from 1 to 15, with a mean of 1.14. On average, retracted papers cover 2.53 subjects and 1.48 fields of study. In addition, 13% of the retracted papers in the sample have at least one author who is affiliated with a US institution. The fractions of papers that have at least one author who is affiliated with a university and a hospital are 87% and 17%, respectively.

Table 2.1: Raw Sample Summary Statistics

	Mean	SD	Maximum	Minimum
Publication year	2012.0	5.31	2021	1980
Retraction year	2014.1	4.98	2021	1980
Months to retraction	26.1	42.12	412	0
Good reasons	0.16	0.36	1	0
Bad reasons	0.29	0.45	1	0
Ugly reasons	0.30	0.46	1	0
Uncertain reasons	0.25	0.43	1	0
Number of authors	3.81	2.86	81	1
Number of subjects	2.53	1.16	10	1
Number of fields	1.48	0.61	5	1
Number of countries	1.14	0.48	15	1
US affiliation	0.13	0.34	1	0
University affiliation	0.87	0.33	1	0
Hospital affiliation	0.17	0.37	1	0
Basic life sciences	0.15	0.36	1	0
Business and technology	0.11	0.32	1	0
Environmental sciences	0.012	0.11	1	0
Humanities	0.0086	0.09	1	0
Physical sciences	0.13	0.34	1	0
Social sciences	0.041	0.20	1	0
Observations		30903		

2.5.2 Results on Factors Affecting Time-to-retraction

Table 2.2 shows the result from estimating equation 2.1 via a negative binomial model. In the baseline model (column 1 and column 5), the number of authors positively correlates with the time-to-retraction. This is consistent with the prior prediction that papers with more authors have greater communication costs when responding to questions from journals. Using the value from column 1, adding one author to papers will increase time-to-retraction by 3.4%, holding other factors constant. The estimate becomes insignificant when types of institutions are added to the model (column 2). Interestingly, the number of fields is negatively correlated with time-to-retraction, while the number of subjects is positively correlated with it. This could mean that papers that are more interdisciplinary in nature usually attract more attention and thus scrutiny from readers. Once controlling the number of fields, papers covering more subjects take a longer time to retract, possibly because they require more knowledge to verify the specific methodologies and results presented than papers covering fewer subject areas. Papers with at least one author that is affiliated with a US institution have a longer time to retract. This result is consistent with the findings by Furman et al. (2012). In addition, having at least one author affiliated with a hospital increases the time-to-retraction.

Table 2.2: Outcome Variable: Time to Retract

	Full sample		Single field		Published before 2015	
	(1)	(2)	(3)	(4)	(5)	(6)
Number of authors	0.0339**	0.0236	0.00270	0.000362	0.102***	0.0206**
	(0.0123)	(0.0121)	(0.00685)	(0.00686)	(0.0217)	(0.00706)
Number of fields	-0.447***	-0.407***			-0.652***	
	(0.0529)	(0.0476)			(0.0647)	
Number of subjects	0.191***	0.157***	0.190***	0.179***	0.225***	0.108***
	(0.0260)	(0.0234)	(0.0491)	(0.0461)	(0.0335)	(0.0195)
Number of countries	0.0939	0.0981*	0.0970*	0.0925*	0.241***	0.209***
	(0.0500)	(0.0492)	(0.0456)	(0.0462)	(0.0668)	(0.0404)
Publication year	-0.0776***	-0.0780***	-0.0806***	-0.0823***	-0.122***	-0.102***
	(0.00717)	(0.00696)	(0.00814)	(0.00818)	(0.0116)	(0.00431)
US affiliation	0.295***	0.341***	0.122	0.137	0.565***	0.482***
	(0.0823)	(0.0855)	(0.0912)	(0.0963)	(0.101)	(0.0550)
University affiliation		-0.0368		0.100		-0.00839
		(0.0817)		(0.0730)		(0.0561)
Hospital affiliation		0.317***		0.135		0.205***
		(0.0739)		(0.0774)		(0.0349)
Basic life sciences			-0.0493	-0.0813		0.445***
			(0.162)	(0.176)		(0.0967)
Health sciences			-0.00842	-0.0461		0.677***
			(0.146)	(0.144)		(0.0986)
Physical sciences			-0.342***	-0.343***		0.136
			(0.0972)	(0.0966)		(0.109)
Environmental sciences			-1.234*	-1.234*		-1.462***
			(0.487)	(0.485)		(0.216)
Humanities			0.366**	0.377**		0.752***
			(0.134)	(0.131)		(0.164)
Business and technology			-0.923***	-0.920***		-1.328***
			(0.165)	(0.166)		(0.111)
Observations	30903	30903	17739	17739	20314	11064

Notes: Robust standard errors are clustered at journal level and are reported in parentheses.
The first coefficient in column 1 (0.0339) reveals that with one additional author, the time-to-retraction increases by (exp(0.0339)-1)*100=3.4%, keeping everything else constant.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In addition, the publication year is negatively correlated with time-to-retraction, suggesting that either the speed of discovering false science or the speed of responding to mistakes in papers (or both) has increased over the years. When only looking at columns 1 through 4, one may suggest that the negative correlation between publication year and time-to-retraction arises from the selection bias of including papers that retracted quickly in more recent years. In other words, many papers published in recent years could potentially take a long time to retract and thus are not observed at the time of my study. Similar to the approach used by Furman et al. (2012), I repeat the analysis using papers that were published before 2015, producing similar results as shown in columns 5 and 6. This confirms that there has been a decrease in time-to-retraction over the years.

After refining the dataset to papers with only one field, I also examine the differences by fields of study. As shown in columns 3, 4, and 6, papers in environmental sciences and business and technology take less time to retract than those in the base group social sciences. Papers in humanities take longer to retract. The coefficients on basic life sciences, health sciences, and physical sciences are insignificant in the sample covering the full period but significant and positive in the sample of papers published before 2015. In Table B.2 of Appendix B, I present the results from estimating the equations via log transformation. Specifically, papers with 0 month-to-retraction are placed with 0.01 month-to-retraction. The results appear to be largely similar to the negative binomial estimation.

2.5.3 Results on Factors Affecting the Degree of Misconduct

Table 2.3 presents the results for 2.2 estimated via a linear probability model. Overall, increasing the number of authors and countries increases the probability of papers having clearly stated reasons for the reactions, holding the number of fields and author affiliations constant. This means that the involvement of more players makes it harder to hide the reason for misconduct. Associating with more fields decreases the likelihood of papers having clearly stated retractions reasons. The publication year is positively correlated with the probability of having a clear disclosure of retraction reasons, indicating that there has been an improvement in communicating the details of retractions over the years. Having at least one author who is affiliated with a US institution also increases the likelihood of having a clearly stated reason, holding other factors constant. Having at least one author who is affiliated with a hospital also increases the probability of having a clearly stated reason for retraction, although the effect becomes insignificant after controlling for fields. Interestingly, having at least one author who is affiliated with a university decreases the probability of having a clearly stated reason for retraction.

Compared to social sciences, papers in environmental sciences and business and technology are less likely to have clearly stated reasons for retractions. The other fields, such as physical sciences, humanities, and basic life sciences, are not significantly different from social sciences in terms of the probability in disclosing clear retraction reasons.

Table 2.3: Outcome Variable: Retraction Reason Salience

	(1)	(2)	(3)
Number of authors	0.0173***	0.0140***	0.00375
	(0.00317)	(0.00313)	(0.00249)
Number of fields	-0.152***	-0.136***	0
	(0.0206)	(0.0195)	(.)
Number of subjects	0.0279**	0.0162	0.0189
	(0.00945)	(0.00908)	(0.0137)
Number of countries	0.0173	0.0214*	0.0296*
	(0.00898)	(0.00972)	(0.0127)
Publication year	0.0114***	0.0107***	0.00719***
	(0.00179)	(0.00174)	(0.00187)
US affiliation	0.180***	0.190***	0.114***
	(0.0235)	(0.0239)	(0.0275)
University affiliation		-0.0898***	-0.0348
		(0.0256)	(0.0246)
Hospital affiliation		0.107***	0.0305
		(0.0263)	(0.0308)
Basic life sciences			0.0210
			(0.0549)
Health sciences			-0.0120
			(0.0426)
Physical sciences			-0.0550
			(0.0367)
Environmental sciences			-0.153***
			(0.0460)
Humanities			0.0632
			(0.0586)
Business and technology			-0.0943***
			(0.0271)
Observations	30904	30904	17739

Notes: Robust standard errors are clustered at journal level and are reported in parentheses. The first coefficient in column 1 reveals that with one additional author, the probability of having a known reason for retractions increases by 1.73% holding other things unchanged.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.4 shows the results from estimating equation 2.5 using papers with good retraction reasons as the base group. The coefficients represent correlations between the independent variables and the log odds of transitioning from the good reason type to each of the other reason types. The first four columns use the full dataset of retracted papers, while the last two columns include papers that are listed under a single field of study.

Overall, increasing the number of authors increases the probability of papers falling into the ugly group from the good group. For example, the estimate in the second column indicates that for each additional author added, the multinomial log odds for the ugly group to the good group will increase by 0.0534 while holding other factors constant. In other words, with the addition of one author, the relative risk of being retracted for serious misconduct is about 1.05 times as compared to being retracted for minor issues, holding other things unchanged. Associating with more fields and having at least one author affiliated with a US institution does not seem to affect the likelihood of papers falling into all other reason groups instead of the good reason group. After controlling for the number of fields, having more subjects seem to increase the likelihood of bad and ugly papers as opposed to papers with good retraction reason.

Table 2.4: Outcome Variable: Retraction Reason Type

	Full sample		Full sample		Single field	
	(1)		(2)		(3)	
	bad	ugly	bad	ugly	bad	ugly
Number of authors	-0.00154	0.0534**	-0.00641	0.0355*	0.0119	0.0526**
	(0.0120)	(0.0164)	(0.0144)	(0.0177)	(0.0200)	(0.0198)
Number of fields	0.0216	-0.189	0.0287	-0.151		
	(0.101)	(0.121)	(0.0845)	(0.103)		
Number of subjects	0.117*	0.255**	0.107**	0.209***	0.128***	0.186*
	(0.0462)	(0.0797)	(0.0338)	(0.0631)	(0.0385)	(0.0886)
Number of countries	-0.0574	-0.217*	-0.0682	-0.244*	-0.0782	-0.334**
	(0.0839)	(0.103)	(0.0821)	(0.106)	(0.0872)	(0.110)
Publication year	-0.0137	-0.0739**	-0.0152	-0.0796**	-0.00575	-0.0804***
	(0.0228)	(0.0237)	(0.0243)	(0.0251)	(0.0212)	(0.0225)
US affiliation	0.129	0.0820	0.129	0.110	0.213	0.261
	(0.118)	(0.151)	(0.114)	(0.151)	(0.111)	(0.148)
University affiliation			0.277	0.685**	0.240	0.526*
			(0.222)	(0.227)	(0.210)	(0.227)
Hospital affiliation			0.0986	0.441*	0.211	0.942***
			(0.200)	(0.224)	(0.172)	(0.220)
Basic life sciences					-0.0933	0.496
					(0.205)	(0.317)
Health sciences					-0.540**	-0.770**
					(0.177)	(0.281)
Physical sciences					-0.187	0.252
					(0.133)	(0.248)
Environmental sciences					0.122	1.221
					(0.283)	(0.740)
Humanities					0.546*	-0.409
					(0.241)	(0.684)
Business and technology					0.191	1.074**
					(0.279)	(0.352)
Constant	27.89	149.0**	30.76	160.0**	11.82	161.3***
	(45.93)	(47.77)	(48.84)	(50.32)	(42.52)	(45.21)
Observations	23079		23079		14228	

Notes: Robust standard errors are clustered at journal level and are reported in parentheses.
The first coefficient in the second column (0.0534) indicates that for each additional author added, the multinomial log odds for the ugly group to the good group will increase by 0.0534 while holding other factors constant. In other words, with the addition of one author, the relative risk of being retracted for serious misconduct is about exp(0.0534)=1.05 times as compared to being retracted for minor issues, holding other things unchanged.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The publication year is negatively correlated with the log odds for bad and ugly groups to the good group, indicating that there fewer papers are being retracted for serious misconduct over the years. This may reflect a reduction in actual serious misconduct in sciences or a decrease in effectiveness in catching serious misconduct. It is hard to distinguish between the two clearly using this empirical setup. Having at least one author who is affiliated with a hospital or a university increases the probability of papers falling into the ugly group from the good group, keeping other things constant. Again, this may indicate that these authors have more serious wrongdoings, or that universities and hospitals are better at catching more serious misconduct.

Compared to social sciences, papers in basic life sciences and business and technology are more likely to be retracted for ugly reasons instead of good reasons, while papers in health sciences are less likely to be retracted for bad or ugly reasons instead of good reasons. Physical sciences and environmental sciences are not significantly different from social sciences in terms of having different levels of misconduct.

2.5.4 Results on Impact of Retractions on Citation Counts

Table 2.5 shows the summary statistics of the matched sample, including the retracted papers and their matched neighbor articles used as a control group. In the working sample, there are 1308 retracted papers and 2395 control papers. All papers were published between 1955 and 2014 and retracted papers were retracted between 1960 to 2015. The total citation counts received per paper range from 1 to 1029 for retracted papers and 1 to 7177 for control papers. On average, control papers receive more total citations (115.1) than retracted papers (57.3). A similar pattern is observed for average annual citations received by papers, with control papers having a higher annual citation count (6.53) than retracted papers (3.26). The maximum annual citation received by control papers is 65, while that by retracted papers is only 27. Looking at the raw data information, it shows that retracted papers generally receive fewer citations than non-retracted control papers.

Table 2.5: Working Sample Summary Statistics - Cited Papers

	Control				Retracted			
	Mean	SD	Maximum	Minimum	Mean	SD	Maximum	Minimum
Retraction Year					2007.9	8.15	2015	1960
Publication Year	2003.9	8.07	2014	1955	2004.0	8.09	2014	1955
Total Citation	115.1	272.40	7177	1	57.3	86.43	1029	1
Avg. Annual Citation	6.53	15.50	407.4	0.015	3.26	5.02	53.9	0.015
Observations	2395				1308			

The estimated results via PPML using equation 2.6 are reported in Table 2.6. The first four columns present the regressions using the full working sample of matched retracted and control papers. The last four columns show results after refining the sample to papers that have received at least one citation before retraction. Overall, retraction had decreased the annual citation counts as indicated by the negative and significant estimates on the dummy variable Post Retraction. For example, the estimate in column 1 reveals that retraction leads to about 71.2% ($(1 - exp(-1.245)) * 100$) reduction in annual citation counts received. This is consistent with the previous findings by Furman et al. (2012).

The reduction of annual citation counts is greater for papers retracted for bad and ugly reasons than for those retracted for good reasons. This indicates that papers with serious misconduct and ethical issues are punished more severely than those with honest mistakes. The reduction is also greater for papers retracted for known reasons than for those with unknown reasons. This implies that having ambiguous and undisclosed reasons in the retraction process may shield papers from readers' scrutiny or punishment when citing the retracted works.

By focusing on retracted papers with only a single field and their matched controls, I investigate the differential impact of retractions on citations across different fields of study. Columns 4 and 8 show that papers in basic life science and physical science experienced much greater reductions in annual citation counts after retraction than those in social sciences. Papers in the other fields also experienced reductions, but the magnitudes are not statistically different from those in social sciences. The estimations using data from Google Scholar are reported in Table B.3. As shown in the table, the results are very similar.

Table 2.6: Outcome Variable: Annual Citation Counts

	Full Sample				Conditional on Having Pre-retraction Citations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Retraction	-1.245***	-0.727***	-0.654***	-0.327	-1.269***	-0.737***	-0.678**	-0.320
	(0.0559)	(0.128)	(0.195)	(0.260)	(0.0591)	(0.136)	(0.213)	(0.292)
Post Retraction*Certain		-0.547***				-0.561***		
		(0.134)				(0.142)		
Post Retraction*Bad			-0.697***				-0.721**	
			(0.205)				(0.222)	
Post Retraction*Ugly			-0.664**				-0.651**	
			(0.204)				(0.222)	
Post* Basic life sciences				-0.973***				-0.990***
				(0.262)				(0.293)
Post* Health sciences				-0.214				-0.214
				(0.276)				(0.306)
Post* Physical sciences				-1.473***				-1.530***
				(0.291)				(0.323)
Post* Environmental sciences				-0.236				-0.225
				(0.337)				(0.379)
Post* Business and technology				-0.0790				-0.0855
				(0.278)				(0.307)
Paper FEs	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y	Y	Y
N	70503	70503	65131	25304	57948	57948	53662	21608
N cluster	1308	1308	1226	711	1052	1052	990	560
N full	70535	70535	65163	25381	57960	57960	53674	21641

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
The estimate in column (1) reveals that retraction leads to (1-exp(-1.245)=71.2% reduction in annual citations.

Some journals may pick the best or the most influential paper to be the lead paper of the issue, and thus make them different from their neighbors in terms of perceived or actual quality. I repeat the analysis after excluding retracted papers that are the lead papers in their issues and present the results in Table B.4. The results remain the same.

2.5.5 Results on event study of retractions

Figure 2.1 shows the event study plot for the retracted papers that have received some citations before retraction and their control papers. The plot shows the estimates of $\{\delta_k\}_{k=-G-L_G-1}^{k=M+L_M}$ from equation 2.7 on the y-axis and years to retractions on the x-axis with a 95 percent confidence interval on each estimate. The estimates are normalized such that the coefficient at $k = -1$ is 0. The number in parenthesis on the y-axis represents the sample mean of the annual citations one year before retraction. The figure shows that the coefficient becomes significantly negative at the year of retraction. The cumulative effect of retraction remains significant and negative in the years following retraction.

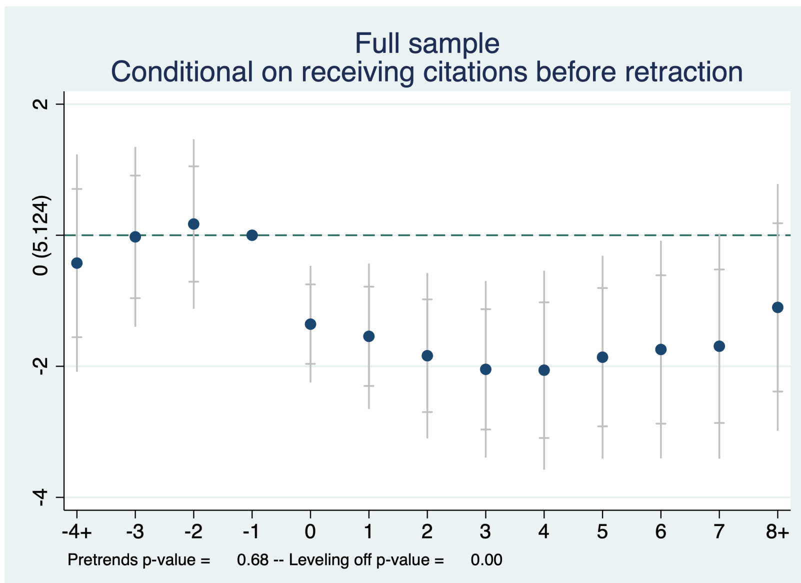

Figure 2.1: Event Study Plot: Full Sample

Figure 2.2 shows the event study plots for a sub-sample of retracted and control papers by reasons of retraction conditional on receiving some citations before retractions. Papers that are retracted due to serious misconduct see the clearest path of reduction in annual citations, with negative and significant estimates across the years after retraction. The plots for papers that are retracted for less severe reasons also show reductions in annual citations, but the trend is less obvious. As for papers that are retracted for unknown reasons, the graph shows no clear sign of a reduction in citations. These plots confirm the findings from the PPML estimates in section 5.4. The event study plots for all retracted and control papers are shown in Figures B.1 and B.2 of Appendix B. The results are very similar to those from the sub-sample.

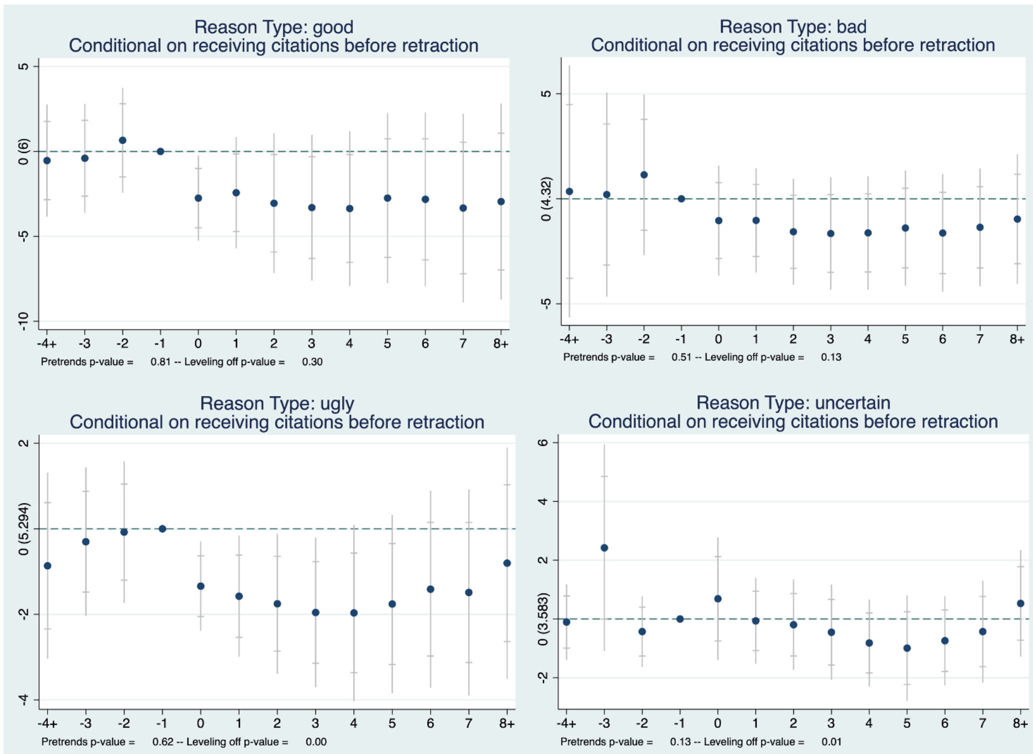

Figure 2.2: Event Study Plots: By Reason

2.6 DISCUSSION

The results suggest that retraction decreases the annual citations received by papers. This show that the retraction system effectively notifies follow-on readers about the problems found in the retracted papers. The impact is greater for papers that are retracted due to severe misconduct than those with milder mistakes or unknown reasons. This could mean that false science and scientific misconduct are punished by the academic community to some extent. It is noteworthy that although annual citation counts have decreased after retraction, however, they did not decrease to zero. In fact, as shown in Figure 2.3, some retracted papers that received no citations at all started to receive citations after retraction. Since retraction is a mechanism for removing papers with substantial errors or misconduct that invalidate the main conclusions of papers, one should expect the follow-on papers to stop citing the retracted papers unless they explicitly acknowledge the retractions. Therefore, it remains puzzling as to why and how the papers continue to be cited.

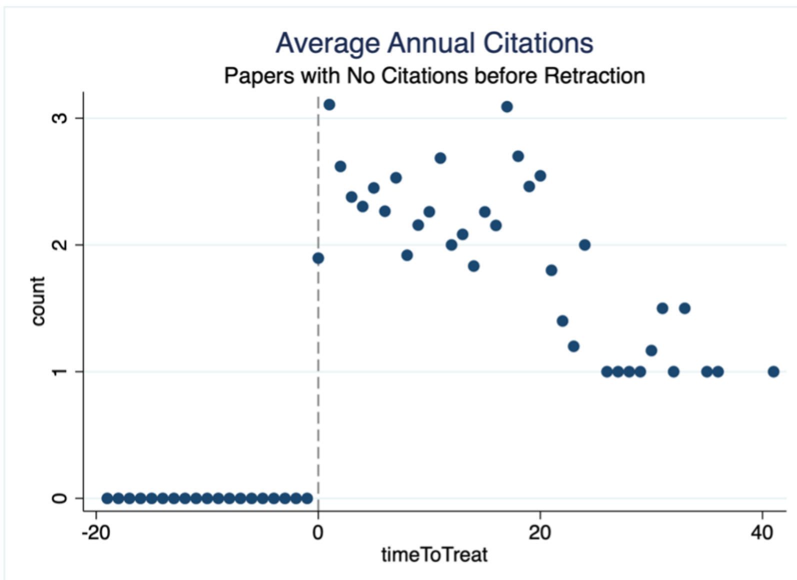

Figure 2.3: Annual Average Citations for Papers with No Pre-Retraction Citations

Citation counts have been used to measure the influence of the cited works, but they do not tell the full stories about the papers' achievements for various reasons. First, citing papers could cite their references with different goals and sentiments. A negative citation that questions the validity of the findings in the referenced papers could serve as a warning to readers and even lead to investigations of misconduct and retractions thereafter. If retraction is truly effective in informing the academic community about the mistakes, we would observe more negative citations from the citing papers after retraction. Second, citations reveal not only the validity and influence of the referenced works but also the quality of the citing works and the practice of referencing in general. Therefore, it is very valuable to evaluate the citation sentiments in addition to citation counts, especially considering the impact of retraction.

2.7 CONCLUSION

Using a unique dataset of retracted papers collected by Retraction Watch and various econometric models, I investigate the factors associated with the time to retraction and reasons for retraction. I find that the number of authors positively correlates with time-to-retraction, possibly due to increased communication costs when having more authors. Papers with at least one author that is affiliated with a US institution have a longer time to retract and are more likely to be revealed with clear reasons for retractions. The number of fields is negatively correlated with time-to-retraction, while the number of subjects is positively correlated with it. Compared to papers in social sciences, papers in environmental sciences and business and technology take less time, while papers in humanities take longer to retract. papers in environmental sciences and business and technology are less likely to be retracted for bad or ugly reasons instead of uncertain reasons, while papers in health sciences are more likely to be retracted for good reasons instead of uncertain reasons, compared to papers in social sciences. Having at least one author who is affiliated with a hospital also increases the probability of having a clearly stated reason for retraction, although the effect becomes insignificant after controlling for fields. Interestingly, having at least one author who is affiliated with a university decreases the probability of having a clearly stated reason for retraction. In addition, the publication year is negatively correlated with time-to-retraction, suggesting that either the speed of discovering false science or the speed of responding to mistakes in papers (or both) has increased over the years. It is also evident that there has been improvement in clearly stating retraction reasons over the years.

Following Furman et al. (2012), I use the nearest neighbor article approach, I provide plausibly causal evidence on the impact of retractions on annual citation counts through a DID framework. I find retraction decreases the annual citations received by papers, and the impact is greater for papers that are retracted due to severe misconduct than those with milder mistakes or unknown reasons. However, the citation counts did not decrease to zero. I discuss the limitations of using citation counts alone to measure the influence of retracted papers and the efficiency of knowledge governance. In the next chapter, I will investigate further on this matter by focusing on the trends in citation sentiments.

CHAPTER 3

How Good Are the Citations? – An Investigation of Citation Sentiments and Retractions

3.1 INTRODUCTION

The system of references has been an important building block of scientific production as scholars contribute to the existing knowledge of mankind. In the context of retraction, referencing also plays an important role in facilitating the discovery of false science and communicating corrections of knowledge to the scientific community and beyond. In Chapter 2, I use a unique dataset on retracted papers and their citation history to analyze the factors affecting retractions, and the impact of retractions on annual citation counts received. The results revealed that retractions decreased annual citation counts across all fields, but not to zero. It remains unclear why and how people cite these retracted papers, and specifically, how retractions have affected citation sentiments of the citing papers. In fact, although citation counts are often used to measure the influence or success of scholars and their publications, the mere count of citations for a paper only provides limited information on the true stand that citing papers take regarding their references. In this chapter, I investigate the relationship between citation sentiments and retractions in pre- and post-retraction periods.

Using a unique database of citation contexts, I collect the contexts in which the retracted papers and control group are cited in the citing papers. The textual information in the contexts is then analyzed using a state-of-art rule-based model to determine the citation sentiments of the citing papers to referenced papers. Specifically, I categorize the citing papers into five mutually exclusive groups: explicit positive, implicit positive, neutral, implicit negative, and explicit negative. I show that there is a sharp increase in explicit negative citations and a moderate increase in implicitly negative citations for retracted papers before retractions. While implicitly positive and neutral citations increase slightly for retracted papers before retraction, their explicit positive citations drop sharply before retractions. Through a staggered DID framework, I also provide causal evidence that retractions decrease all types of citations significantly, even after controlling for the annual total citation counts. The reductions in all types of citations are also greater for papers in the bad and ugly categories than those in the good category, with the magnitudes varying across disciplines. In addition, while the various types of citation counts do not correlate significantly with time-to-retraction, the numbers of non-neutral citations received in the year of publication are all significantly and positively correlated with log odds of the bad and ugly categories to the good category. Explicit negative citations, in which the citing papers provide direct contradictory findings against the retracted papers, play an important role in revealing the nature of the mistakes or misconduct.

The rest of the paper is organized as follows. Section 2 provides background information and a review of related literature on false science and retraction. Section 3 introduces the datasets I use for my analysis. Section 4 specifies in detail the empirical models I employ. Section 5 presents the results of my analysis and discussions on them. Section 6 concludes the paper.

3.2 BACKGROUND AND RELATED LITERATURE

3.2.1 Citation Malpractices

Referencing is a key mechanism through which scholars acknowledge others' work, engage in formal scientific discussions, and connect their contributions to the field of study. Citation counts are often used as an important measure of influence and even the success of published works. We often think of citations as reflections of the quality or relevancy of the cited works, with limited scrutiny of the validity and appropriateness of the citations themselves. Unfortunately, mistakes and malpractices in citation or referencing do exist. In the most extreme cases, citation malpractices involve manipulating citations through coerced citations and citation rings. For instance, in 2020, Kuo-Chen Chou, a biophysicist and founder of the Gordon Life Science Institute, in Boston, USA, was discovered to have coerced authors of papers he edited to cite many of his works and even suggested changing the papers' titles to mention his publications (Lockwood, 2020). He was later banned from the board of the *Journal of Theoretical Biology* for "scientific misconduct of the highest order" (Lockwood, 2020). In 2014, SAGE retracted 60 articles from the *Journal of Vibration and Control* following a 14-month investigation that found evidence for a "peer review and citation ring" centered around Peter Chen, a professor in Taiwan. The investigation leads to the resignation of Taiwan's education minister Chiang Weiling because of his connection to Chen (Lockwood, 2020). In addition, a group of authors invented an algorithm to identify potential citation cartels, which are defined to be groups of authors that cite among themselves disproportionately more than they cite other authors working on the same subject (Fister et al., 2016).

Perhaps the more common types of substandard citation practice involve citation errors, quotation errors, and citing without adequate reading of the original articles. As explained by Smith & Cumberledge (2020), citation errors include "typographical violations of citation styles, excessive or redundant citations, missing citations". In contrast, quotation errors refer to situations where the actual content of the references does not substantiate the cited propositions in the citing texts (Smith & Cumberledge, 2020). In their recent study, Smith and Cumberledge randomly sampled the 250 most cited articles in the top 5 general science journals in 2017 and reviewed their referenced articles. They found that 25% of their citations contain quotation errors and mentioned that this result aligns with previous discoveries of quotation errors in physical, life, and social sciences in similar studies (Smith & Cumberledge, 2020). We know relatively less about how prevalent the practice of citing without adequate reading is. In 2003, Simkin and Roychowdhury published a method for estimating the fraction of authors who cite papers that have actually read them, by counting the repeated misprint in reference lists (Simkin & Roychowdhury, 2003). In their subsequent study, they used data on misprints in citations to 12 high-profile papers, and showed that "about 79-90% of scientific citations are copied from the lists of references used in other papers" (Simkin & Roychowdhury, 2012).

Retractions provide a unique opportunity for us to examine how good people's citations are. By investigating the relationship between retractions and citation sentiments to retracted papers, my study provides additional insights into the literature on citation malpractice from a different angle.

3.2.2 Inadvertent Spread of Retracted Papers

Retractions are issued when the main results of the articles are no longer reliable due to major mistakes or academic misconduct. Ideally, journals should send clear and strong signals to readers via retraction notices, and readers should avoid citing these works unless they explicitly acknowledge the retractions. In reality, many retracted papers are still cited after they are retracted. In Chapter 2 of this dissertation, I present the results that retractions decrease the annual citation counts of the retracted papers, but not to zero. In fact, there were some papers in my dataset with no citations before retractions that started to get citations after retractions. This is consistent with the findings in many studies (Steen, 2011; Teixeira da Silva & Dobránszki, 2017; Bar-Ilan & Halevi, 2018; Schneider et al., 2022). The inadvertent spread of retracted works is harmful to intellectual communities. Analyzing a citation network of a retracted paper, van der Vet & Nijveen (2016) showed that directly citing retracted papers is the main source of propagation of false results.

Some researchers have taken a closer look and investigated if the citing papers mentioned the retraction status of their references. In a case study of long-time post-retraction citations to a fraudulent clinical trial report, Schneider et al. (2020) found that 96% of post-retraction citations did not mention retraction, while 41% of these citations described the retracted paper in detail. Similarly, Bornemann-Cimenti et al. (2016) followed citations of another high-profile retracted paper and found that only 25.8% of the citations mentioned the retraction status. Interestingly, although the citation counts dropped after retraction, the fraction of citing papers that mention retraction status also decreased. In contrast to these results, two studies tracking the citations to the infamous retracted paper in Lancet about the MMR vaccine and autism showed that it is a large fraction of the post-retraction citations acknowledge the retraction status (Suelzer et al., 2019; Heibi & Peroni, 2021). In their studies, they also showed that negative citations increased after the retraction.

A few more studies have also investigated the citation sentiments of citing papers to retracted works. Bar-Ilan & Halevi (2017) evaluated the citation sentiments to a sample of retracted papers from ScienceDirect and found that most of the citations were positive. Furman et al. (2012) conducted a manual analysis of a subset of twenty retracted articles in their sample. They find that in the pre-retraction period, only a few citing papers raise skepticism about the validity of the results in the later retracted papers. In the post-retraction period, they conclude that "fewer than 50% of post-retraction citations built unknowingly on false knowledge".

Most of these studies focus on a small sample of retracted papers and provide little comparisons across subjects or reasons for retraction. My study greatly contributes to this literature by providing rich evidence based on large datasets and rigorous econometric models.

3.2.3 Development in Sentiment Analysis

My study also relates to citation sentiment analysis in a broader context. Some studies have investigated various factors associated with citation sentiments at a large scale. To study the relationship between authors' status changes and citation sentiments they receive, Yan et al. (2020) analyzed over 40 thousand citations to 25 articles written by Nobel Prize laureates in their corresponding prize-winning topics and 75 control group papers that are similar in citation counts and close in publication year. They found moderate increases in positive sentiments toward Nobel articles after the award, while such increases were not observed in the control sample (Yan et al., 2020). Using a set of sentiment lexicons, Dehdarirad & Yaghtin (2022) identified the sentiments of over 115 thousand citing papers to about 17 thousand cited papers in biomedical sciences to investigate the gender differences in citation sentiments. They found that male authors received a higher positive sentiment in citations than their female counterparts. In addition, female authors have a lower tendency to use positive words when citing papers by other female authors, while male authors tend to cite other male authors more positively. Some studies have focused on the special role that negative citation plays in the referencing system. For example, Xu et al. (2022) studied over 40 thousand citations to works on Support Vector Machines (SVM) from 1995 to 2020, and found that there has been no impact of receiving negative citations on the cited papers' literature impact, measured by annual citation counts.

With the development of techniques in text mining, machine learning, and natural language processing, sentiment analysis has been a growing field of research. It has many applications in academic and non-academic settings, such as analyzing social media posts and customer reviews. Recently, citation sentiment analysis has become a new domain in the sentiment analysis field and attracted many computer scientists to develop algorithms and tools for it. There have been many studies exploring the methodologies in extracting citation contexts and training models for sentiment analysis especially tailored for analyzing citations (Abu-Jbara et al., 2013; Goodarzi et al., 2014; Yousif et al., 2019; Budi & Yaniasih, 2023). My study enriches this literature by combining a rule-based sentiment analysis method with rigorous econometric models to provide useful evaluations of factors related to and affecting citation sentiments.

3.3 DATA

3.3.1 Retraction and Control Group Data

I start with the dataset of retracted papers collected and shared by Retraction Watch, as described in Chapter 2. The dataset is considered the largest and most comprehensive of its kind and provides rich information about the retracted papers. Specifically, it contains paper titles, DOIs, authors, dates of publication and retraction, institutions, detailed reasons for retraction, fields, and subjects. More details of the dataset are explained in section 3.1 of Chapter 2.

To investigate the impact of retractions on citation sentiments through a DID framework, I need a set of comparable non-retracted papers as a control group. I use the neighbor article approach as used in section 4.3 of Chapter 2. The control group consists of the nearest neighbor articles published in the same issue and journal in which the retracted paper appears. I searched and collected these papers manually by going to their journals' databases and locating the corresponding issue.

3.3.2 Citation Context Data

To identify the sentiments and opinions of the authors of the citing papers, it is crucial to accurately obtain the citation contexts, which are the text bodies of the citing papers that describe the referenced paper. Given the large number of citing papers in my sample, it is impossible to manually locate the citation statements and surrounding contexts. Fortunately, Scite.ai provides a searchable database of scholarly articles and the textual contexts of their citing papers. Scite is a tool developed by Nicholson et al. (2021) that aims to provide qualitative and quantitative measures of citations to papers. They obtain full-text articles in PDF files through open access and agreement with publishers and convert them into analyzable text data to identify the in-text citations. They locate and extract the sentences that make the citations, as well as a few sentences before and after the location where a paper is cited. These citation contexts are then linked to the referenced papers to form a database of citation networks. They have constantly been processing and adding new papers to the database. As of 2021, they have analyzed over 25 million full-text scientific articles, and the database contained more than 880 million citation statements (Nicholson et al., 2021). The metadata of all citing papers of the included cited papers are recorded in the database, however, not all citation context snippets are available due to restricted access.

They also provide classifications of the citation contexts by the intent of citation through a deep learning model. Specifically, they categorize the citation contexts into groups of "supporting", "contrasting", and "mentioning" based on rhetorical intentions, indicating if the citing papers provide direct evidence in support, or contrast to the cited papers, or simply just mention the references. These categories do not reflect citation sentiment or judgment based on opinions, but the intentions of citation based on direct comparisons of the scientific results between the citing and cited papers. An additional "unclassified" group is reserved for citation contexts that are written in non-English languages. They used annotations by scientists who are experienced in interpreting scientific papers in their original training data in the deep learning method. Based on the manual annotations, they estimated "the average distributions of the citation statements as 92.6% mentioning, 6.5% supporting, and 0.8% contrasting statements" (Nicholson et al., 2021). Although the classification measure is not perfect, they argued that their methods outperform many others, achieving F-scores of 0.648, 0.59, and 0.973 for supporting, contrasting, and mentioning categories, respectively.

Using their searchable database, I manually collected the citation contexts to the papers in my working sample, including both the retracted papers and their control group. The final dataset contains information on classifications of citation contexts, and other metadata, including authors, titles, journals, publishers, and years of publication. In addition, for papers with available citation context snippets, the sections of papers in which the citation contexts appear are also recorded. More interestingly, the Scite measures, i.e, the number of supporting, contrasting, and mentioning citations, are also available for most of the citing papers. Using this information, I categorized the citation contexts further by sentiments.

3.4 EMPIRICAL STRATEGY

3.4.1 Identification of Citation Sentiment

With the citation contexts I obtained from scite.ai, I categorized them further by their sentiments toward the referenced papers. Specifically, I define five groups of citation contexts: explicit positive, implicitly positive, neutral, implicitly negative, and explicit negative. The explicit positive and negative citations refer to cases where the citing papers directly compare results between the references and their results. The "supporting" and "contrasting" citation contexts from Scite.ai fit into these two categories. The remaining "mentioning" citation contexts, which comprise most of my data, are further divided into three groups: implicitly positive, neutral, and implicitly negative. Implicit positive (or negative) citations refer to scenarios where in the citing papers, authors give positive (or negative) comments about the reference or mention that the reference is in agreement (or disagreement) with other works in the existing literature. The neutral category is reserved for citations that only mention the topic or results in the referenced paper, with no additional comments or comparisons with other papers. The specific definitions and examples of the categorization are presented in Figure 3.1.

	Definition	Method	Example
Explicit Positive	Provide supporting evidence for the cited work.	Scite Supporting	"Our results are in agreement with one previous report (cite)"
Implicit Positive	No direct evidence; but use positive words or mention there's agreement in literature	Scite Mentioning + Positive words (agree, same, interesting, remarkable etc.)	"There are numerous interesting advancements…(cite)"
Neutral	Simply stating the topic or results without any comment or comparison	Scite Mentioning + No key words found	"PCR analysis of offspring was performed (cite)"
Implicit Negative	No direct evidence; but use negative words or mention there's disagreement in literature	Scite Mentioning + Negative words (disagree, differ, shocking, disprove etc.)	"There is also disagreement among studies as to which Notch receptors and target genes are functionally significant in OSA."
Explicit Negative	Provide contrasting evidence for the cited work.	Scite Contrasting	"This result is in striking contrast to other humanized mouse models, in which HTLV-1 infection…."

Figure 3.1: Definition of Citation Sentiment

Since I have around 300 thousand citation contexts in my working sample, the key challenge is efficiently and accurately labeling sentiments at a large scale. To do so, I use a rule-based algorithm to automate the categorization process. This approach has been used widely in sentiment analysis of various textual data, such as media posts, customer reviews, and scholarly articles. The advantage of such a method over a machine-learning algorithm is that it does not require extensive learning/training of computer programs, which could be time-consuming. The key idea behind a rule-based algorithm is to use an underlying sentiment lexicon, a list of words that are pre-labeled with sentiment orientations, to identify the sentiment of target texts. There are several sentiment lexicons developed and widely used to either categorize words into binary groups of sentiments or assign words with valence scores to indicate sentiment intensity. Some examples include LIWC, GI, Hu-Liu04, ANEW, SentiWordNet, SenticNet, and VADER.

In my analysis, I use VADER's lexicon and semantic programming to label citation sentiments. The VADER model was developed by C.J Hutto and Eric Gilbert from the Georgia Institute of Technology to perform sentiment analysis on social media texts. According to Hutto and Gilbert (2014), their model not only keeps the advantages of traditional sentiment lexicons (large, straightforward, and easily extendable), but also provides gold-standard quality that has been validated by humans. They also developed tools to incorporate linguistic features such as degree modifiers and contrastive conjunction in the analysis. I obtained their publicly available codes and sources through the Python Natural Language Toolkit platform.

Hutto and Gilbert have shown that the model performs well, especially on social media texts. However, the linguistic features and vocabulary choices in social media texts and scholarly writings could differ greatly. For example, words like "arguing" would get a negative sentiment in the social media context, but neutral in the context of scholarly writing. In addition, the expressions of disagreement or distaste are much more subtle in scholarly writing. To improve the compatibility of the VADER lexicon with citation contexts, I added a list of words that scholars commonly use to express confirmation, doubt, agreement, disagreement, and interest. I also removed colloquially words and symbols that would only appear in social media texts. Using this modified lexicon, I analyze the citation contexts in the "mentioning" category to assign to each of them either an "implicit positive", "implicit negative", or neutral sentiment. Figure 3.2 illustrates my data processing steps.

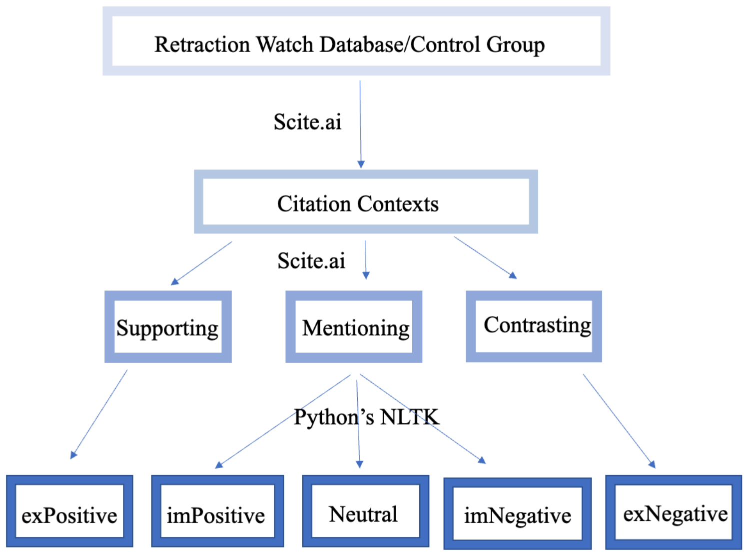

Figure 3.2: Identification of Citation Sentiment

To evaluate the accuracy of this approach, I manually labeled 150 contexts that were randomly drawn from the pool of "mentioning" citation contexts. I then measured the model's accuracy by calculating the fraction of correct labels out of 150 contexts for each category. The results for the original VADER model and the modified version are reported in Table 3.1. As shown in the table, the probabilities of correctly identifying all three sentiment groups are greatly improved after modifications, especially for the neutral and implicit negative groups. The performance is comparable to other rule-based classification approaches, with a significant advantage in identifying negative sentiments (Yan et al., 2020).

Table 3.1: Accuracy of VADER Models

	Implicit Positive	Neutral	Implicit Negative
Original	40.3%	39.4%	12.5%
Modified	54.7%	61.3%	78.0%
N (Ground Truth)	63	61	26

Note: The table shows the fraction of correct labels out of 150 contexts that were randomly drawn from the pool of "mentioning" citation contexts.

Many citing papers in my data contain multiple citation contexts towards the same referenced paper. The average citation context counts per citing paper are 2.7 for retracted papers and 2.8 for the control group. For citing papers with multiple citation contexts, I combine the sentiments of the citation contexts by assigning the aggregate sentiment in the following priority order: explicit negative, explicit positive, implicitly negative, implicitly positive, neutral, and unknown(in non-English or with unavailable snippets). For example, if a citing paper contains an explicit negative context, an implicitly positive context, and an unknown citation context about the same referenced paper, I assign explicit negative as its overall citation sentiment to that reference.

3.4.2 Citation Sentiments and Time-to-retraction

"False science", which is subsequently retracted is often discovered in a crowd-sourcing manner and first communicated through informal channels. Although less commonly used by scholars as the first resort to voice concerns about scholarly works, citations are important and formal channels in which scholars engage in academic discussions. It is intriguing to study the role of formal citations in flagging problematic results in published works. Specifically, it is interesting to see if receiving more negative citations predisposes papers to retract faster. To study this, I will estimate the following specification:

$$TimeToRetract_{ij} = \alpha + \beta c_i + \Gamma X_i + \epsilon_{ij} \tag{3.1}$$

where $TimeToRetract_{ij}$ is the number of months for each paper i in journal j to retract after publication. c_i is the number of negative citations received by paper i in the year of publication. X_i is a vector of paper-level covariates, including the number of authors, the number of fields, the number of subjects that the paper is associated with according to the categorization by Retraction Watch, the number of countries in which the authors' affiliated institutions belong, type of institutions, and the year of publication. Since the dependent variable is a count variable and highly skewed with a large number of small values, I estimate the specification through a negative binomial model. I cluster robust standard errors at the journal level to account for correlations in retraction speed within journals.

3.4.3 Citation Sentiments and Retraction Reasons

Since I have information on the reasons for retraction, as described in Chapter 2, it is also interesting to see if having different types of citations in the year of publication predisposes retracted papers to a) clearly reveal reasons for retractions and b) fall into groups of more severe misconduct.

To study the first question, I will estimate the following model:

$$D_{ij} = \alpha + \beta c_i + \Gamma X_i + \epsilon_{ij} \tag{3.2}$$

where D_{ij} is an indicator of retracted paper i from journal j having a certain reason for retraction. c_i is the number of negative citations received by paper i in the year of publication. X_i is a vector of paper-level covariates as described in equation 3.1. Robust standard errors are clustered at the journal level.

To investigate the second question, I use a MNL model to investigate the determinates affecting the probability that a retracted paper falls into different categories by reason types. The sample includes all the retracted academic papers with certain reasons for retractions. In the analysis, the dependent variable is a discrete variable that takes four unordered and independent reason types: good ($r = 1$), bad ($r = 2$), and ugly ($r = 3$). The probability that paper i belongs to any of the reason types r is conditional on a set of P paper-level variables (x_i) and is represented by the following equation:

$$\pi_r(x_i) = P(y = r|x_i) = \frac{\exp(x_i\beta_r)}{1 + \sum_{k=1}^{3} \exp(x_i\beta_k)} \tag{3.3}$$

for

$$r = 2, 3$$

and

$$\pi_1(x_i) = P(y = 1|x_i) = \frac{1}{1 + \sum_{k=1}^{3} \exp(x_i\beta_k)} \tag{3.4}$$

I use the good reason type ($r = 1$) as the base category and estimate the following specifications:

$$\log[\frac{\pi_r(x_i)}{\pi_1(x_i)}] = \beta_0 + \beta_{1r}x_{1i} + \beta_{2r}x_{2i} + ... + \beta_{Pr}x_{Pi} \tag{3.5}$$

where

$$r = 2, 3$$

The parameters of interest β_{ir} are estimated by the method of maximum likelihood. The independent variables used are similar to those in 3.1. I include citation counts by sentiments in the independent variables and discuss their corresponding coefficients. Robust standard errors are clustered at the journal level.

3.4.4 Impact of Retractions on Citation Sentiment

In Chapter 2, I showed that annual citation counts decrease after retractions, but not to zero. In this chapter, I evaluate the impact of retractions on citation sentiments by estimating the following equation via DID framework:

$$\mathbb{E}[y_{ict}|X_{ict}] = exp[\alpha + \beta PostRetraction_{ict} + \mu_i + \lambda_t + \gamma_i + \epsilon_{it}] \tag{3.6}$$

where y_{it} is the annual count of explicit positive, implicit positive, neutral, implicit negative, and explicit negative citations received by retracted paper i in year t. $PostRetraction_{it}$ is a dummy variable that is equal to 1 after retraction, and 0 before retraction or never retracted. μ_i, λ_t, γ_i are paper, year, and paper's age fixed effects. The fixed effects control for many time-invariant characteristics that could affect citations, such as journal prestige. Robust standard errors are clustered at the retraction case level c (the groups of retracted papers and their corresponding control papers). The identification of this model follows the same logic as in the DID specification in Chapter 2. I estimate the coefficient via a Poisson Pseudomaximum likelihood (PPML) model as described previously in Chapter 2.

In theory, if retractions are well-communicated in the science community, and scholars carefully check their references, it is expected that scholars cite retracted works more critically. In particular, we should observe a reduction in positive citations and an increase in negative citations to retracted papers after retractions, keeping the total annual citations constant. The relative magnitude of change in explicit and implicit sentiments is not clear. Explicit positive or negative citations are given if the authors of the citing papers have direct evidence for or against the referenced papers, while implicit positive and negative citations are given when authors indirectly compare works in the literature. On the one hand, retractions may lead to higher fluctuations in implicit sentiments of citing papers than in explicit sentiments, as the latter requires substantiations based on scientific findings. In other words, scientists should give explicit negative citations to retracted papers regardless of their retraction status. On the other hand, authors pay more attention to the papers that they are making direct comparisons with and hence may be aware of the retraction status of their references.

In addition, I expect to see a greater reduction in positive citations and a larger increase in negative citations for retracted papers with more severe misconduct or mistakes. It would still be reasonable, although not optimum, to cite a paper that was retracted because editors accidentally published it twice. However, it would be less acceptable if authors continue to speak highly of the results of a paper after it is found to be fraudulent and unreliable.

3.5 RESULTS

3.5.1 Descriptive Statistics

Table 3.2 shows the breakdown of different sentiment types of citing papers to control and the retracted papers. Looking at the proportions, the retracted papers have slightly more explicit negative citations and fewer explicit positive ones than those in the control group. Retracted papers have a smaller proportion of implicit negative, implicit positive, and neutral citations than their counterparts in the control group. Retracted papers are cited by a higher fraction of non-English papers and papers with no available citation contexts.

Table 3.2: Working Sample Summary Statistics - Citing Papers

	Control Percent	Retracted Percent
Context Not Available	36.10	43.40
Context Not in English	0.91	1.12
Explicit Negative	0.30	0.35
Explicit Positive	2.83	2.21
Implicit Negative	9.23	7.45
Implicit Neutral	9.42	7.58
Implicit Positive	41.20	37.88
Total	100.00	100.00
Observations	368006	96046

Figures 3.3 and 3.4 show raw data plots of the annual citation counts by sentiment categories. The vertical axis represents the average annual citation counts by each category, and the horizontal axis shows the time to retraction. The sample only includes papers that received at least one citation before retractions. As shown in the plots, there is a steep increase in explicit negative citations and a decrease in explicit positive citations before retractions. This shows that citing papers are important in signaling the problems of later-retracted works before the retractions. The average annual counts of implicit negative, neutral, and implicit positive citations rise slightly before retraction, indicating the increasing attention received by the retracted papers before retractions. All types of citations drop right after retraction, including negative citations. This reveals that it may be a more common practice to stop citing retracted papers than citing them negatively.

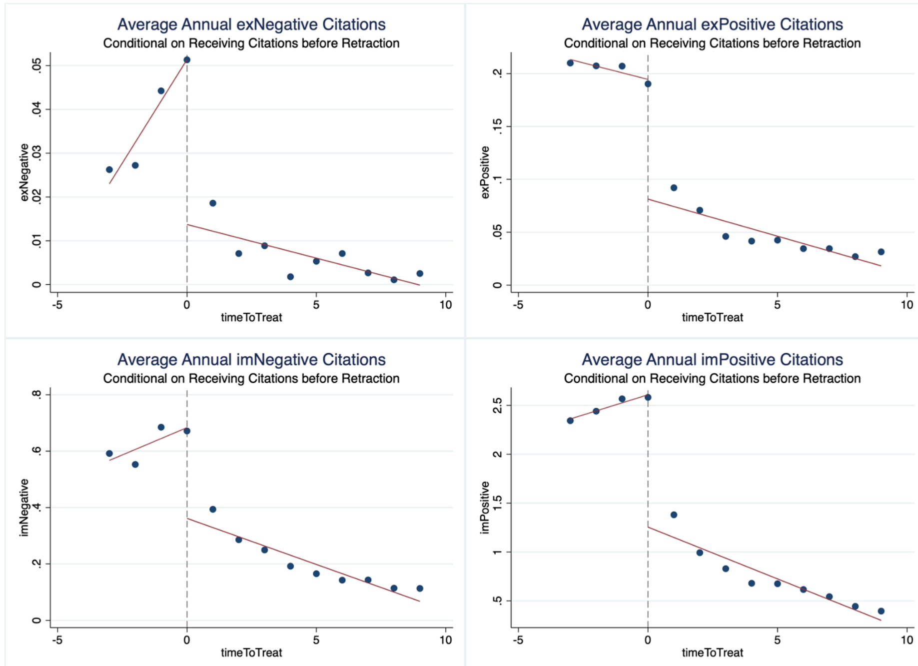

Figure 3.3: Raw Plot of Average Annual Citation by Sentiments -P1

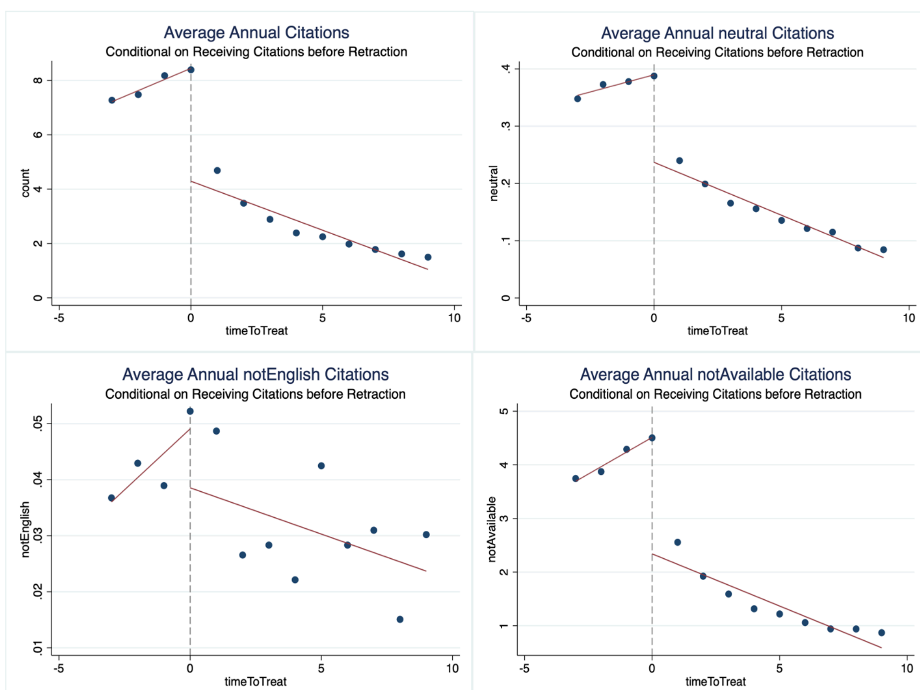

Figure 3.4: Raw Plot of Average Annual Citation by Sentiments -P2

3.5.2 Results on Correlations between Citation Sentiments and Time-to-retraction

Table 3.3 shows the results for estimating equation 3.1. The outcome variable is time-to-retraction, and the independent variable is the number of various citation counts by sentiments received in the year of publication. As shown in the table, these citation counts do not correlate significantly with time-to-retraction. Table C.1 in Appendix C presents the estimation results via log transformations, which generate the same conclusion.

Table 3.3: Outcome Variable: Time-to-retraction

	(1)	(2)	(3)	(4)	(5)	(6)
Total Cites in 1st Year	-0.00387					
	(0.00638)					
exPositive Cites in 1st Year		-0.0319				
		(0.0672)				
imPositive Cites in 1st Year			-0.0163			
			(0.0124)			
Neutral Cites in 1st Year				-0.0543		
				(0.0458)		
imNegative Cites in 1st Year					-0.0489	
					(0.0385)	
exNegative Cites in 1st Year						0.0963
						(0.164)
Observations	1418	1418	1418	1418	1418	1418

Notes: Robust standard errors are clustered are journal level, reported in parenthesis.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

3.5.3 Results on Correlations between Citation Sentiments and Retraction Reasons

Table 3.4 presents the results for estimating equation 3.2. The outcome variable is an indicator of having certain reasons for retractions. As shown in columns 6 and 7, the number of explicit negative citations received in the 1st year after publication is significantly and positively correlated with the probability of having a certain reason for retraction later. This is true after holding a host of controls and the number of other types of citations received, as shown in the table. This shows that explicit negative citations, in which the citing papers provide direct contradictory findings against the retracted papers, play an important role in revealing the nature of the mistakes or misconduct. The other types of citations do not seem to affect reason status significantly.

Table 3.4: Outcome Variable: Reason Status (Certain vs Uncertain)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total Cites in 1st Year	0.00268*						0.00317
	(0.00121)						(0.00262)
exPositive Cites in 1st Year		-0.00867					-0.0238
		(0.0153)					(0.0203)
imPositive Cites in 1st Year			0.00576				-0.00412
			(0.00384)				(0.00780)
Neutral Cites in 1st Year				0.0264			0.0100
				(0.0236)			(0.0242)
imNegative Cites in 1st Year					0.0234		0.0129
					(0.0127)		(0.0115)
exNegative Cites in 1st Year						0.0608**	0.0411**
						(0.0204)	(0.0137)
Number of Author Control	Y	Y	Y	Y	Y	Y	Y
Number of Fields Control	Y	Y	Y	Y	Y	Y	Y
Number of Subjects Control	Y	Y	Y	Y	Y	Y	Y
Number of Country Control	Y	Y	Y	Y	Y	Y	Y
Publication Year Control	Y	Y	Y	Y	Y	Y	Y
Univeristy Affiliation Control	Y	Y	Y	Y	Y	Y	Y
Hospital Affiliaion Control	Y	Y	Y	Y	Y	Y	Y
N	1418	1418	1418	1418	1418	1418	1418

Notes: Robust standard errors are clustered are journal level, reported in parenthesis.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 3.5 presents the results for estimating equation 3.5 using papers with good retraction reasons as the base group. The coefficients represent correlations between the various citation counts received in the year of publication and the log odds of transitioning from the good reason type to each of the other reason types. All estimations include many controls, as shown in the table. Overall, receiving more non-neutral citations in the year of publication increases the likelihood of a paper falling into the bad and ugly categories from the good category. This is especially true for explicit negative citations. There are two potential explanations for this result. First, the non-neutral citations reflect the level of scrutiny received by the retracted papers. As more people are making direct or indirect comparisons between the retracted papers and other works, it is easier t discover more serious mistakes or misconduct related to them. Second, papers with more serious misconduct often make bolder claims than others and thus receive more attention and citations commenting on their results.

Table 3.5: Outcome Variable: Reason Types

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	bad	ugly	bad	ugly	bad	ugly	bad	ugly	bad	ugly	bad	ugly	bad	ugly
Total Cites in 1st Year	0.142	0.155*											-0.0262	0.0240
	(0.0737)	(0.0741)											(0.0763)	(0.0839)
exPositive Cites in 1st Year			1.548*	1.412*									1.221	1.057
			(0.703)	(0.694)									(0.748)	(0.747)
imPositive Cites in 1st Year					0.454**	0.455**							0.401*	0.279
					(0.151)	(0.151)							(0.195)	(0.202)
Neutral Cites in 1st Year							0.610	0.926					0.124	0.437
							(0.644)	(0.611)					(0.653)	(0.634)
imNegative Cites in 1st Year									0.934*	0.933**			0.644	0.574
									(0.364)	(0.338)			(0.398)	(0.360)
exNegative Cites in 1st Year											12.17***	12.07***	11.34***	11.25***
											(0.354)	(0.403)	(0.542)	(0.447)
Number of Author Control	Y		Y		Y		Y		Y		Y		Y	
Number of Fields Control	Y		Y		Y		Y		Y		Y		Y	
Number of Subjects Control	Y		Y		Y		Y		Y		Y		Y	
Number of Country Control	Y		Y		Y		Y		Y		Y		Y	
Publication Year Control	Y		Y		Y		Y		Y		Y		Y	
Univeristy Affiliation Control	Y		Y		Y		Y		Y		Y		Y	
Hospital Affiliaion Control	Y		Y		Y		Y		Y		Y		Y	
N	1318		1318		1318		1318		1318		1318		1318	

Notes: Robust standard errors are clustered are journal level, reported in parenthesis.

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

3.5.4 Results on Impact of Retractions on Citation Sentiment

Tables 3.6 shows the baseline results from estimating equation 3.6 for each type of citation count as the outcome variable. The "unknown" category includes citing papers with non-English and unavailable citation contexts. Overall, retractions decrease all types of citations significantly, even after controlling for the annual total citation counts. For example, the estimate in column 1 reveals that retraction leads to about 75.3% ($(1 - exp(-1.397)) * 100$) reduction in annual explicit positive citation counts received, holding annual total citations constant. This result is consistent with the observations based on the raw data plots in the previous section. This suggests that scholars tend to stop citing retracted papers in general, instead of citing them negatively.

I repeat the estimations for the sub-sample of retracted papers that have received at least one citation before retractions and obtain similar results, shown in Table C.2 Appendix C. For some papers in the data, the citation contexts of all citing papers to them are not available. After excluding these papers, the results remain similar, as shown in Table C.3 Appendix C.

Table 3.6: Outcome Variable: Annual Citation Counts by Sentiment

	ExPositive	ImPositive	Neutral	ImNegative	ExNegative	Unknown
Post Retraction	-1.397***	-1.191***	-1.126***	-1.116***	-1.521***	-1.045***
	(0.113)	(0.0607)	(0.0645)	(0.0968)	(0.220)	(0.0731)
Paper FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y	Y
N	40523	63957	46908	54195	13941	69589
N cluster	1094	1294	1157	1231	582	1307
N full	70535	70535	70535	70535	70535	70535

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* p<0.1, ** p<0.05, *** p<0.01

Table 3.7 and Table 3.8 show the impact of retractions by reason status (certain vs uncertain) and reason types (good, bad, ugly). Overall, disclosing clear reasons for retractions leads to greater reductions in all types of citation counts except neutral citations. The reductions in all types of citations are also greater for papers in the bad and ugly categories than those in the good category. These results are similar to the findings about the overall annual citation counts in Chapter 2. This reveals that follow-on citations are very sensitive to the reasons for retractions. Therefore, disclosing clearly the reasons for retractions can effectively stop the inadvertent spread of misinformation in scientific productions. These results hold well after zooming into the subsamples of papers with pre-retraction citations and papers with at least one citing a paper with available citation contexts, as reported in Table C.4, C.5, C.6,C.7 in Appendix C.

Table 3.7: Impact of Annual Citation Sentiment Counts by Reason Status

	ExPositive	ImPositive	Neutral	ImNegative	ExNegative	Unknown
Post Retraction	-0.866**	-0.618***	-0.900***	-0.455**	-1.072	-0.713***
	(0.331)	(0.174)	(0.197)	(0.165)	(0.958)	(0.128)
Post Retraction*Certain	-0.558	-0.603***	-0.238	-0.694***	-0.455	-0.352*
	(0.346)	(0.183)	(0.204)	(0.188)	(0.974)	(0.140)
Paper FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y	Y
N	40523	63957	46908	54195	13941	69589
N cluster	1094	1294	1157	1231	582	1307
N full	70535	70535	70535	70535	70535	70535

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* p<0.1, ** p<0.05, *** p<0.01

Table 3.8: Impact of Annual Citation Sentiment Counts by Reason Types

	ExPositive	ImPositive	Neutral	ImNegative	ExNegative	Unknown
Post Retraction	-1.089***	-0.541***	-0.256	-0.529***	-0.0130	-0.708***
	(0.278)	(0.130)	(0.209)	(0.131)	(0.493)	(0.203)
Post Retraction*Bad	-0.194	-0.701***	-1.001***	-0.648***	-1.723**	-0.301
	(0.321)	(0.156)	(0.226)	(0.174)	(0.557)	(0.219)
Post Retraction*Ugly	-0.526	-0.769***	-0.945***	-0.700***	-1.577**	-0.461*
	(0.315)	(0.149)	(0.222)	(0.183)	(0.597)	(0.219)
Paper FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y	Y
N	37757	59180	43767	50264	13146	64255
N cluster	1026	1212	1087	1157	554	1225
N full	65163	65163	65163	65163	65163	65163

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 3.9 presents additional results on the differential impact of retractions by fields of study. The sample includes papers that are only associated with one field of study, and excludes papers in humanities and environmental sciences as there are too many zeros in the annual counts of different types of citations for these two fields. Explicit negative citations are also excluded for the same reason. The base group includes papers in social sciences. Overall, retracted papers in physical sciences experience a greater reduction in all non-neutral citation sentiment counts than those in social sciences. Papers in basic life sciences also have a greater reduction in implicit positive and implicit negative citations after retraction compared to social sciences. In addition, papers in business and technology (including economics) have a smaller reduction in explicit positive and neutral citations after retraction than those in social sciences. Similar results are found in the subsamples as shown in Tables C.8 and C.9 of Appendix C.

Table 3.9: Impact of Annual Citation Sentiment Counts by Fields

	ExPositive	ImPositive	Neutral	ImNegative	Unknown
Post Retraction	-0.734	-0.298	-0.810	-0.568*	-0.129
	(0.525)	(0.307)	(0.559)	(0.266)	(0.184)
Post* Basic life sciences	-0.788	-0.978**	-0.292	-0.672*	-0.876***
	(0.541)	(0.313)	(0.563)	(0.278)	(0.200)
Post* Health sciences	0.490	-0.0724	0.458	0.307	-0.441*
	(0.593)	(0.328)	(0.602)	(0.296)	(0.211)
Post* Physical sciences	-1.573*	-1.442***	-0.850	-1.153***	-1.296***
	(0.629)	(0.328)	(0.587)	(0.314)	(0.233)
Post* Business and technology	1.863*	0.454	1.201	0.737	-0.435*
	(0.864)	(0.369)	(0.820)	(0.412)	(0.212)
Paper FEs	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y
N	17510	24509	19993	22475	25269
N cluster	592	706	623	669	711
N full	25381	25381	25381	25381	25381

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

3.6 CONCLUSION

In this chapter, I extend the results in Chapter 2 and investigate further the relationship between retractions and citation patterns, focusing on citation sentiments. Using a unique collection of citation contexts of the citing papers to the retracted and control papers, and a state-of-art rule-based model and pre-training machine learning model, I categorize citation sentiments of the citing papers into five mutually exclusive groups: explicit positive, implicit positive, neutral, implicit negative, and explicit negative. I show that there is a sharp increase in explicit negative citations and a moderate increase in implicitly negative citations for retracted papers before retractions. While implicitly positive and neutral citations increase slightly for retracted papers before retraction, their explicit positive citations drop sharply before retractions. In addition, while the various types of citation counts do not correlate significantly with time-to-retraction, the numbers of non-neutral citations received in the year of publication are all significantly and positively correlated with the log odds of the bad and ugly categories to the good category. This is particularly true for explicit negative citations, in which the citing papers provide direct contradictory findings against the retracted papers. Explicit negative citations also play an important role in revealing the nature of the mistakes or misconduct.

Through a staggered DID framework, I also provide causal evidence on the impact of retractions on citation sentiments. Overall, retractions decrease all types of citations significantly, even after controlling for the annual total citation counts. The reductions in all types of citations are also greater for papers in the bad and ugly categories than those in the good category. The magnitudes of reductions differ across disciplines. For example, retracted papers in physical sciences experience a greater reduction in all non-neutral citation sentiment counts than those in social sciences.

These results revealed that negative citations are important in discovering false science and raising concerns about published works. The reduction in negative citations following retractions is surprising, indicating that scholars tend to avoid citing retracted at all, instead of citing them negatively.

APPENDIX A

Supplementary Materials for Chapter 1

A.1 APPENDIX A TABLES

Table A.1: First Stage Results Using A Subset of Collin and Margo's data

	Severity Group	Severity Group	Severity Group	Severity Group	Severity Index
Rainfall, April 1968	-0.134**	-0.145*	-0.141**	-0.129**	-0.0173*
	(0.0459)	(0.0594)	(0.0471)	(0.0458)	(0.00710)
City manager	-0.165	-0.123	-0.154		-0.0303
	(0.164)	(0.172)	(0.164)		(0.0183)
Percent black in 1960	3.289***	3.107***	3.325***	3.423***	0.427**
	(0.671)	(0.717)	(0.687)	(0.663)	(0.139)
Population in 1960	0.000000220***	0.000000226**	0.000000218**	0.000000233**	3.20e-08
	(6.27e-08)	(6.90e-08)	(6.42e-08)	(6.91e-08)	(1.96e-08)
Northeast	0.492	0.456	0.525*	0.563*	0.0201
	(0.255)	(0.267)	(0.252)	(0.213)	(0.0296)
MidWest	0.514**	0.513**	0.516**	0.546***	0.0498
	(0.157)	(0.173)	(0.157)	(0.157)	(0.0305)
West	0.396	0.530	0.383	0.405	0.0584
	(0.270)	(0.326)	(0.271)	(0.287)	(0.0375)
Rainfall, annual avg.		-0.00208			
		(0.00960)			
Rainfall, April avg.		0.115			
		(0.107)			
Rainfall, April 1967		-0.0310			
		(0.0491)			
Value Trend 1950-1960			0.551		
			(0.602)		
N	74	74	74	74	74
F	12.11	8.801	10.35	12.52	2.070

Notes: Robust standard errors are in parenthesis. Sample includes all cities in the triple matched data.
* p<0.1, ** p<0.05, *** p<0.01

APPENDIX B

Supplementary Materials for Chapter 2

B.1 APPENDIX B FIGURES

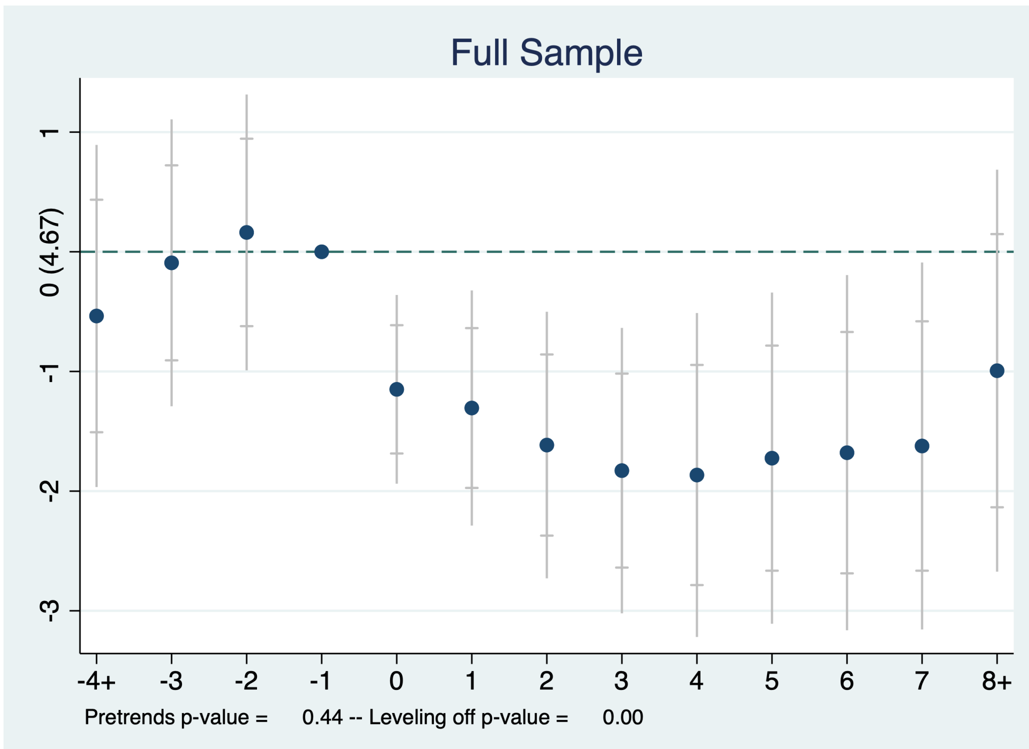

Figure B.1: Event Study Plots: By Reason

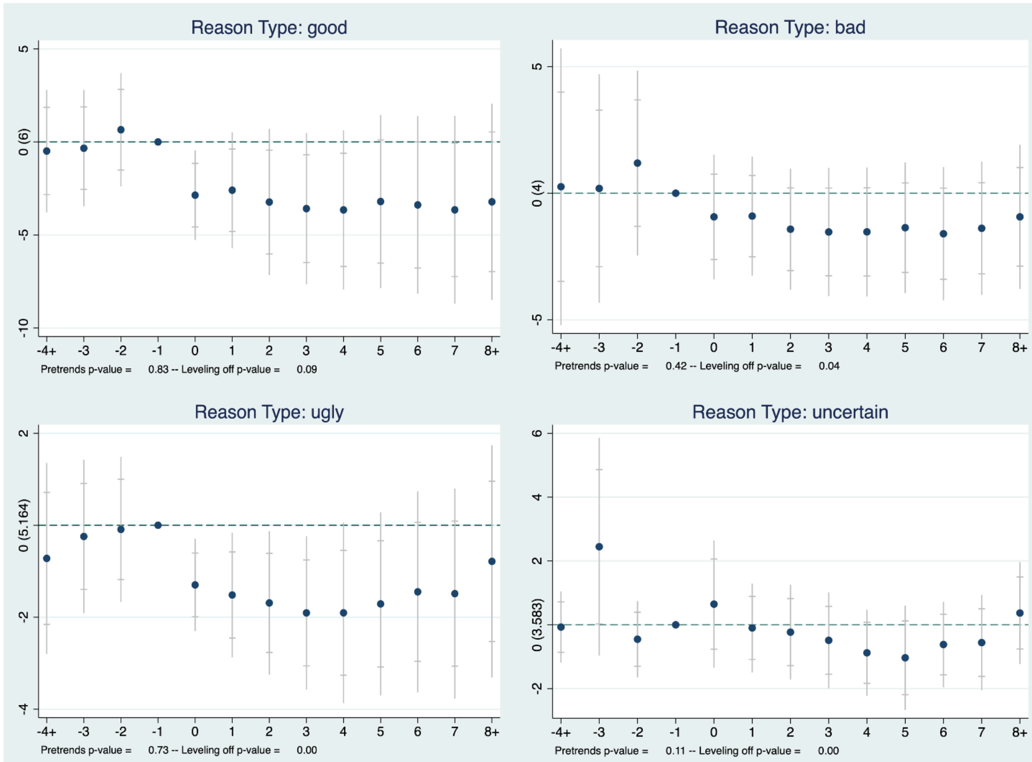

Figure B.2: Event Study Plots: By Reason

Table B.1: Categorization of Reasons for Retractions

Good	Bad	Ugly	Uncertain
Breach of Policy by Third Party	Bias Issues or Lack of Balance	Breach of Policy by Author	Author Unresponsive
Complaints about Company/Institution	Cites Retracted Work	Civil Proceedings	Date of Retraction/Other Unknown
Complaints about Third Party	Concerns/Issues About Authorship	Complaints about Author	Legal Reasons/Legal Threats
Copyright Claims	Concerns/Issues About Data	Criminal Proceedings	No Further Action
Doing the Right Thing	Concerns/Issues About Image	Ethical Violations by Author	Notice _ Lack of
Duplicate Publication through Error by Journal/Publisher	Concerns/Issues about Referencing/Attributions	Euphemisms for Misconduct	Notice _ Limited or No Information
Duplication of Article	Concerns/Issues About Results	Fake Peer Review	Notice _ Unable to Access via current resources
Duplication of Data	Concerns/Issues about Third Party Involvement	Falsification/Fabrication of Data	Updated to Retraction
Duplication of Image	Conflict of Interest	Falsification/Fabrication of Image	Upgrade/Update of Prior Notice
Duplication of Text	Contamination of Cell Lines/Tissues	Falsification/Fabrication of Results	Withdrawal
Error by Journal/Publisher	Contamination of Materials (General)	Hoax Paper	Withdrawn (out of date)
Error by Third Party	Contamination of Reagents	Manipulation of Images	Not Presented at Conference
Ethical Violations by Third Party	Error in Analyses	Manipulation of Results	
Euphemisms for Duplication	Error in Cell Lines/Tissues	Misconduct _ Official Investigation/Finding	
False Affiliation	Error in Data	Misconduct by Author	
Lack of Approval from Author	Error in Image	Paper Mill	
Lack of Approval from Company/Institution	Error in Materials (General)	Publishing Ban	
Lack of Approval from Third Party	Error in Methods	Randomly Generated Content	
Miscommunication by Author	Error in Results and/or Conclusions	Rogue Editor	
Miscommunication by Company/Institution	Error in Text	Sabotage of Materials	
Miscommunication by Journal/Publisher	Euphemisms for Plagiarism	Sabotage of Methods	
Miscommunication by Third Party	False/Forged Authorship	Unreliable Data	
Misconduct by Company/Institution	Informed/Patient Consent _ None/Withdrawn	Unreliable Image	
Misconduct by Third Party	Investigation by Company/Institution	Unreliable Results	
Nonpayment of Fees/Refusal to Pay	Investigation by Journal/Publisher		
Objections by Author(s)	Investigation by ORI		
Objections by Company/Institution	Investigation by Third Party		
Objections by Third Party	Lack of IRB/IACUC Approval		
Original Data not Provided	Plagiarism of Article		
Retract and Replace	Plagiarism of Data		
Salami Slicing	Plagiarism of Image		
Temporary Removal	Plagiarism of Text		
Transfer of Copyright/Ownership	Results Not Reproducible		
Updated to Correction			
Withdrawn to Publish in Different Journal			

Notes: All reason are manually coded by Retraction Watch.

B.2 APPENDIX B TABLES

Table B.2: Outcome Variable: ln(Time to Retract)

	Full sample		Single field		Published before 2015	
	(1)	(2)	(3)	(4)	(5)	(6)
Number of authors	0.0616	0.0334	0.0335	0.0211	0.123*	0.0540***
	(0.0323)	(0.0374)	(0.0190)	(0.0177)	(0.0484)	(0.0116)
Number of fields	-0.607***	-0.509***			-0.619***	
	(0.0762)	(0.0790)			(0.113)	
Number of subjects	0.404***	0.315***	0.472*	0.423*	0.403***	0.388***
	(0.0942)	(0.0715)	(0.203)	(0.179)	(0.101)	(0.0302)
Number of countries	0.170	0.175	0.207	0.197	0.406*	0.383***
	(0.120)	(0.120)	(0.117)	(0.120)	(0.187)	(0.0554)
Publication year	-0.0481**	-0.0546***	-0.0663***	-0.0741***	-0.145***	-0.123***
	(0.0168)	(0.0152)	(0.0188)	(0.0166)	(0.0280)	(0.00596)
US affiliation	0.726**	0.801**	0.430	0.527	1.069***	0.992***
	(0.266)	(0.278)	(0.341)	(0.379)	(0.278)	(0.0751)
University affiliation		-0.0351		0.184		-0.164*
		(0.219)		(0.274)		(0.0736)
Hospital affiliation		0.847***		0.740*		0.709***
		(0.256)		(0.354)		(0.0802)
Basic life sciences			-0.756	-0.915		-0.426**
			(0.730)	(0.793)		(0.137)
Health sciences			-0.386	-0.620		0.681***
			(0.345)	(0.432)		(0.126)
Physical sciences			-0.694*	-0.679*		-0.169
			(0.316)	(0.308)		(0.117)
Environmental sciences			-3.513*	-3.493*		-3.658***
			(1.547)	(1.539)		(0.205)
Humanities			0.720*	0.725*		1.041***
			(0.309)	(0.308)		(0.232)
Business and technology			-1.429***	-1.417***		-1.106***
			(0.200)	(0.203)		(0.101)
Observations	30903	30903	17739	17739	20314	11064

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.3: Impact of Retractions on Citation Counts Using Google Scholar Data

	Full Sample				Conditional on Having Pre-retraction Citations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Retraction	-0.865***	-0.460***	-0.124	-0.337*	-0.864***	-0.463***	-0.198	-0.418*
	(0.0376)	(0.118)	(0.128)	(0.162)	(0.0393)	(0.126)	(0.122)	(0.169)
Post Retraction*Certain		-0.428***				-0.423**		
		(0.124)				(0.131)		
Post Retraction*Bad			-0.741***				-0.664***	
			(0.150)				(0.146)	
Post Retraction*Ugly			-0.822***				-0.735***	
			(0.136)				(0.129)	
Post* Basic life sciences				-0.770***				-0.668***
				(0.174)				(0.180)
Post* Health sciences				-0.0401				0.0611
				(0.180)				(0.186)
Post* Physical sciences				-1.323***				-1.271***
				(0.192)				(0.201)
Post* Environmental sciences				0.771*				0.945**
				(0.317)				(0.361)
Post* Business and technology				0.408*				0.504**
				(0.190)				(0.196)
Paper FEs	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y	Y	Y
N	56136	56136	50601	30613	46075	46075	41793	24465
N cluster	1373	1373	1265	751	1086	1086	1012	578
N full	56142	56142	50607	30619	46081	46081	41799	24471

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.

Table B.4: Impact of Retractions on Citation Counts Using Subsample Excluding Lead Retracted Articles

	Full Sample				Conditional on Having Pre-retraction Citations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Retraction	-1.270***	-0.766***	-0.628**	-0.757***	-1.291***	-0.780***	-0.651**	-0.745***
	(0.0572)	(0.139)	(0.198)	(0.0941)	(0.0601)	(0.148)	(0.214)	(0.101)
Post Retraction*Certain		-0.531***				-0.538***		
		(0.144)				(0.154)		
Post Retraction*Bad			-0.778***				-0.786***	
			(0.206)				(0.222)	
Post Retraction*Ugly			-0.707***				-0.696**	
			(0.207)				(0.222)	
Post* Basic life sciences				-0.565***				-0.590***
				(0.102)				(0.108)
Post* Health sciences				0.226				0.221
				(0.141)				(0.147)
Post* Physical sciences				-1.003***				-1.070***
				(0.168)				(0.174)
Post* Environmental sciences				0.196				0.203
				(0.237)				(0.265)
Post* Business and technology				0.267				0.253
				(0.142)				(0.148)
Paper FEs	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y	Y	Y
N	67035	67035	61869	24142	55410	55410	51222	20717
N cluster	1218	1218	1142	661	990	990	931	524
N full	67067	67067	61901	24218	55422	55422	51234	20752

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.

APPENDIX C

Supplementary Materials for Chapter 3

C.1 APPENDIX C TABLES

Table C.1: Outcome Variable: ln(Time to Retraction)

	(1)	(2)	(3)	(4)	(5)	(6)
Total Cites in 1st Year	0.00633					
	(0.00835)					
exPositive Cites in 1st Year		0.0422				
		(0.0594)				
imPositive Cites in 1st Year			0.0173			
			(0.0170)			
Neutral Cites in 1st Year				0.0521		
				(0.0517)		
imNegative Cites in 1st Year					0.0331	
					(0.0378)	
exNegative Cites in 1st Year						0.243
						(0.213)
Observations	1418	1418	1418	1418	1418	1418

Notes: Robust standard errors are clustered are journal level, reported in parenthesis.

* p<0.1, ** p<0.05, *** p<0.01

C.1.1 Additional Results on Impact of Retraction on Citation Sentiment Counts

Table C.2: Outcome Variable: Annual Citation Counts by Sentiment, Sample: Papers Cited before Retractions

	ExPositive	ImPositive	Neutral	ImNegative	ExNegative	Unknown
Post Retraction	-1.411***	-1.210***	-1.139***	-1.138***	-1.541***	-1.068***
	(0.116)	(0.0621)	(0.0666)	(0.0950)	(0.244)	(0.0747)
Paper FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y	Y
N	36159	54057	41139	46703	12658	57553
N cluster	934	1047	973	1007	525	1052
N full	57960	57960	57960	57960	57960	57960

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* p<0.1, ** p<0.05, *** p<0.01

Table C.3: Outcome Variable: Annual Citation Counts by Sentiment, Sample: Papers with at least some citing papers that have available snippet

	ExPositive	ImPositive	Neutral	ImNegative	ExNegative	Unknown
Post Retraction	-1.314***	-1.107***	-1.052***	-1.032***	-1.438***	-1.145***
	(0.109)	(0.0586)	(0.0637)	(0.0949)	(0.217)	(0.0782)
Paper FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y	Y
N	35336	54088	40436	46346	12699	50500
N cluster	1094	1294	1157	1231	582	1263
N full	59479	59479	59479	59479	59479	59479

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* p<0.1, ** p<0.05, *** p<0.01

Table C.4: Annual Citation Sentiment Counts by Reason Status, Sample: Papers Cited before Retractions

	ExPositive	ImPositive	Neutral	ImNegative	ExNegative	Unknown
Post Retraction	-0.816*	-0.626***	-0.889***	-0.452**	-1.087	-0.730***
	(0.331)	(0.184)	(0.211)	(0.170)	(0.970)	(0.137)
Post Retraction*Certain	-0.627	-0.614**	-0.262	-0.720***	-0.461	-0.356*
	(0.348)	(0.192)	(0.218)	(0.191)	(0.988)	(0.149)
Paper FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y	Y
N	36159	54057	41139	46703	12658	57553
N cluster	934	1047	973	1007	525	1052
N full	57960	57960	57960	57960	57960	57960

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* p<0.1, ** p<0.05, *** p<0.01

Table C.5: Annual Citation Sentiment Counts by Reason Status, Sample: Papers with at least some citing papers that have available snippet

	ExPositive	ImPositive	Neutral	ImNegative	ExNegative	Unknown
Post Retraction	-0.779*	-0.561***	-0.829***	-0.438**	-1.306	-0.716***
	(0.314)	(0.157)	(0.199)	(0.157)	(1.041)	(0.151)
Post Retraction*Certain	-0.564	-0.575***	-0.234	-0.624***	-0.134	-0.455**
	(0.329)	(0.165)	(0.206)	(0.180)	(1.056)	(0.164)
Paper FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y	Y
N	35336	54088	40436	46346	12699	50500
N cluster	1094	1294	1157	1231	582	1263
N full	59479	59479	59479	59479	59479	59479

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* p<0.1, ** p<0.05, *** p<0.01

Table C.6: Annual Citation Sentiment Counts by Reason Types, Sample: Papers Cited before Retractions

	ExPositive	ImPositive	Neutral	ImNegative	ExNegative	Unknown
Post Retraction	-1.113***	-0.559***	-0.255	-0.523***	-0.217	-0.738***
	(0.309)	(0.141)	(0.216)	(0.138)	(0.525)	(0.223)
Post Retraction*Bad	-0.205	-0.708***	-1.040***	-0.684***	-1.501*	-0.295
	(0.352)	(0.168)	(0.233)	(0.180)	(0.596)	(0.239)
Post Retraction*Ugly	-0.499	-0.760***	-0.944***	-0.724***	-1.384*	-0.446
	(0.343)	(0.159)	(0.228)	(0.186)	(0.649)	(0.239)
Paper FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y	Y
N	33688	50162	38528	43480	11907	53285
N cluster	878	985	920	952	501	990
N full	53674	53674	53674	53674	53674	53674

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table C.7: Annual Citation Sentiment Counts by Reason Types, Sample: Papers with at least some citing papers that have available snippet

	ExPositive	ImPositive	Neutral	ImNegative	ExNegative	Unknown
Post Retraction	-1.062***	-0.496***	-0.202	-0.468***	0.0356	-0.733**
	(0.282)	(0.115)	(0.203)	(0.122)	(0.492)	(0.251)
Post Retraction*Bad	-0.164	-0.670***	-0.973***	-0.638***	-1.655**	-0.388
	(0.323)	(0.142)	(0.221)	(0.166)	(0.553)	(0.266)
Post Retraction*Ugly	-0.438	-0.715***	-0.926***	-0.659***	-1.568**	-0.552*
	(0.316)	(0.134)	(0.216)	(0.174)	(0.594)	(0.267)
Paper FEs	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y	Y
N	33019	50163	37809	43111	12003	46939
N cluster	1026	1212	1087	1157	554	1183
N full	55071	55071	55071	55071	55071	55071

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table C.8: Annual Citation Sentiment Counts by Fields, Sample: Papers Cited before Retractions

	ExPositive	ImPositive	Neutral	ImNegative	Unknown
Post Retraction	-0.748	-0.257	-1.074	-0.701*	-0.0816
	(0.591)	(0.323)	(0.720)	(0.308)	(0.178)
Post* Basic life sciences	-0.777	-1.024**	-0.0437	-0.539	-0.928***
	(0.606)	(0.328)	(0.723)	(0.319)	(0.194)
Post* Health sciences	0.498	-0.105	0.763	0.446	-0.477*
	(0.655)	(0.344)	(0.756)	(0.335)	(0.206)
Post* Physical sciences	-1.704*	-1.518***	-0.589	-1.052**	-1.385***
	(0.706)	(0.344)	(0.744)	(0.353)	(0.231)
Post* Business and technology	1.888*	0.399	1.449	0.747	-0.469*
	(0.909)	(0.384)	(0.948)	(0.446)	(0.206)
Paper FEs	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y
N	15567	21042	17669	19513	21594
N cluster	493	558	512	537	560
N full	21641	21641	21641	21641	21641

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* p<0.1, ** p<0.05, *** p<0.01

Table C.9: Annual Citation Sentiment Counts by Fields, Sample: Papers with at least some citing papers that have available snippet

	ExPositive	ImPositive	Neutral	ImNegative	Unknown
Post Retraction	-0.580	-0.175	-0.546	-0.283	-0.156
	(0.514)	(0.277)	(0.525)	(0.227)	(0.247)
Post* Basic life sciences	-0.789	-0.950***	-0.412	-0.811***	-0.911***
	(0.529)	(0.283)	(0.530)	(0.242)	(0.259)
Post* Health sciences	0.456	-0.126	0.271	0.125	-0.377
	(0.578)	(0.296)	(0.568)	(0.259)	(0.282)
Post* Physical sciences	-1.433*	-1.232***	-0.794	-1.166***	-1.433***
	(0.613)	(0.295)	(0.560)	(0.275)	(0.290)
Post* Business and technology	1.112	0.189	0.790	0.208	-0.456
	(0.789)	(0.346)	(0.817)	(0.358)	(0.292)
Paper FEs	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y
Paper's Age FEs	Y	Y	Y	Y	Y
Annual Total Citation Control	Y	Y	Y	Y	Y
N	14848	19089	16526	18179	18865
N cluster	587	697	620	665	691
N full	19304	19304	19304	19304	19304

Notes: Robust standard errors are clustered are treatment and control pair level, and are reported in parenthesis.
* p<0.1, ** p<0.05, *** p<0.01

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