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Essays on Public Policy, Air Quality, and Human Behavior

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ABSTRACT

ESSAYS ON PUBLIC POLICY, AIR QUALITY, AND HUMAN BEHAVIOR

By

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This dissertation consists of three chapters. The first chapter investigates the impact of air quality changes on people's environmental awareness and beliefs which are measured by Google search interests related to air quality and the donation amounts to the Democratic and Republican parties. The increase in air pollutant indicators may influence the public's environmental attention and re-evaluate the incumbent politician's environmental position. I use the fixed effects OLS model and Instrumental Variable method to estimate the effect of air quality change on Google search interests on air quality-related terms and the contribution amount to Democrats and Republicans. Firstly, I find that Google search interests for “air quality”, “air pollution” and “environmental protection” increase by 0.0858 which is 0.3% of the mean search interests, when the average AQI increases by one unit in a month which means people pay more attention to air quality when they experienced worse air quality. People are more likely to have stronger reactions to prolonged changes in air quality compared to temporary deteriorations. Secondly, the poor air quality will lead people to increase their contribution amounts to Democrats while decrease for Republicans. It suggests that bad air quality carries a moderate electoral penalty for anti-environment incumbents as most of the Republicans are more anti-environment compared with Democrats.

In the second chapter, I investigate the benefits of the lockdown policy implemented in response to the emergence of COVID-19 in Wuhan, China in December 2019. The Chinese government enforced strict lockdown measures to contain the spread of the virus, which resulted in economic losses but potentially led to improvements in air quality. Using the Staggered DID model, I examine the impact of the lockdown and its subsequent lifting on air quality outcomes. I use lockdown cities as the treatment group and the non-lockdown cities as the control group. The results reveal that in the cities under lockdown, both the AQI and $\mathrm{PM}_{2.5}$ levels showed significant improvement, with reductions of 6.610 and $2.788\mathrm{ug/m}^3$ respectively, compared to the control cities. Additionally, a daily decrease of 0.239 in AQI and $0.110\mathrm{ug/m}^3$ in $\mathrm{PM}_{2.5}$ was observed from the implementation of the lockdown policy until March 14th, 2020, in the lockdown cities. To ensure the robustness of the findings and rule out the possibility of systematic differences between treatment and control cities, I conduct an event study analysis. The results indicate that both the treatment and control groups exhibited a parallel trend in air quality prior to the implementation of the lockdown, further strengthening the validity of the results.

The third essay studies the impact of piloted carbon market transactions on air quality and mental health. The air pollution caused by the development of the economy has caused huge losses in human and financial costs. Much literature is concerned about the impact of air quality on heart disease, stroke, lung cancer, and other health effects, but less attention is paid to mental health. China's carbon trading market pilots and the national carbon market provide ideal quasi-experiments. In this study, I utilize the DID method to estimate the effects of the ETS on air quality and mental health. The pilot province Fujian Province was treated as the treatment group, and the remaining provinces that never implemented carbon marketing policy in 2013 and 2016, served as the control group. The results reveal a significant improvement in air quality following the implementation of ETS, as indicated by a decrease in AQI by 10.98 units, $PM_{2.5}$ by 7.92 ug/m^3, and PM_{10} by 13.23 ug/m^3. Furthermore, the analysis shows that CESD20 score of individuals in Fujian Province experienced a decrease of 3.7% after the pilot of ETS, indicating a positive impact on mental well-being.

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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DEDICATION

For my parents.

They support and encourage me to do everything that I want to do.

They are the most supportive and open-minded parents.

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1.1 Introduction

Although the air quality in the United States has improved significantly in the past few decades, it still poses great hazards to human health. $PM_{2.5}$ is a crucial indicator for measuring air quality. It refers to particulate matter that has a diameter of 2.5 micrometers or smaller, specifically those small enough to be inhaled into the respiratory system. The average value of PM2.5 ranged from $37\mathrm{ug/m^3}$ in 1980 to $12\mathrm{ug/m^3}$ in 2012 which exceeds the annual average concentration standard value $10\mathrm{ug/m^3}$ for abnormally sensitive people.

The attention of voters in air pollution and environmental protection are crucial for several reasons. Firstly, environmental protection voters in environmental protection are critical to the success of environmental protection efforts and the resolution of global environmental issues. Google Search Interests on Air Quality (GSIAQ) and voter's donation to different political parties may provide a useful proxy for voter and legislator concerns because Democrats and Republicans hold different views on environmental protection. Democrats are generally more active on environmental issues and advocate for more stringent environmental regulation policies, while Republicans tend to be more conservative on environmental policy, believing that such policies, including air pollution control, may hinder economic growth and employment and deny global climate change. For instance, Edward Scott Pruitt, who served as the fourteenth Administrator of the Environmental Protection Agency (EPA) during the Donald Trump presidency[1], was known for his controversial stance on environmental issues, including global

[1] https://www.cbsnews.com/news/epa-chief-says-carbon-dioxide-not-a-primary-cause-of-global-warming/#:~:text=EPA%20chief%20says%20carbon%20dioxide%20not%20a%20primary%20cause%20of%20global%20warming&text=WASHINGTON%20%2D%2D%20The%20new%20chief,consensus%20and%20his%20own%20agency

warming.

This paper studies the impact of air quality on Google search behavior and donation behavior related to environmental protection. Specifically, I investigate the effect of air quality on public attention to environmental issues using the GSIAQ as a proxy, as well as its impact on political donations to Democrats and Republicans. Air quality changes are primarily assessed through API (Air Pollutant Indicators) such as the AQI (Air Quality Index), $PM_{2.5}$, O_3, SO_2, NO_2, and CO.

The most relevant literature to this paper is Liao and Junco (2022) and Yao et al. (2022). Liao and Junco (2022) study the impact of temperature on people's beliefs in climate change. The primary difference lies in the fact that Liao and Junco (2022) examine the impact of extreme temperature on people's belief in climate change, while I focus on the impact of air quality changes on people's attitudes towards environmental protection. In contrast to Liao et al. (2022), I not only use a revealed preference approach to study air quality shocks on people's beliefs in environmental protection but also incorporate low-stake outcomes such as GSIAQ. With the increasing rates of internet usage in recent years, Google search volume data have become a popular tool for tracking public interests (Jun et al. 2018) and can serve as an indicator of how people respond to social issues, including economic activities (Choi and Varian 2012), epidemic diseases (Dugas et al. 2013), public policy (Shirky 2011), and natural disasters (Kam et al. 2019). By using the GSIAQ as a proxy for salience, I aim to identify the effect of air quality on the relevance of environmental protection in the eyes of the public. As Google search behavior requires minimal effort and costs, it is more likely to reflect people's attention to environmental protection compared to donation behavior. Yao et al. (2022) study the impact of air quality on people's trust in the government in China with IV method. Rather than focusing on developing countries, my research is based on the United States which can provide some insights on developed countries. Furthermore, while their paper focuses on the effect of air quality on people's trust in the government based on survey data, my research uses donation data, which is considered a more reliable source of information.

The purpose of this paper is to examine the relationship between air quality and two important indicators of public concern and action on environmental protection: GSIAQ and donations to Democrats and Republicans. I got GSIAQ from Google Trends. Air quality data is obtained from the United States Environmental Protection Agency database, while online contribution data are taken from the Database on Ideology, Money in Politics, and Elections. I explore the long-term effect of air quality on GSIAQ from 2006 to 2022 as Google Search behavior is a low-stake and immediate behavior. Using a baseline fixed-effects OLS model and optimized IV model, I study the impact of air quality on donations in 2014. OLS method typically have strict assumptions, and the presence of unavoidable measurement errors in air quality may affect the results, so I also employed IV method. In addition, I extend the model to include air quality data from one week to one month prior to the donations to test for lagged or accumulated effects. This allows me to examine whether past changes in air quality have an impact on current donations or if people respond immediately to air quality. I also monitor heterogeneous effects, such as the heterogeneous effects on counties that are controlled by pro-environmental or anti-environmental politicians. I use the League of Conservation Voters (LCV) score of incumbents to represent their environmental views. I also study the heterogeneous effect in counties that the local economy rely on polluting firms or not.

To the best of my knowledge, this is the first paper to empirically test the impact of air quality changes on people's attitudes towards environmental protection. While Liao et al. (2022)

have examined the causal relationship between extreme temperature and weather fluctuations on people's beliefs about climate change, I focus on the impact of air quality-related indexes on people's donations to different political parties and their attitudes towards environmental protection. The second contribution is that I combined two important indicators of public concern and action on environmental protection: GSIAQ and online donations to Democrats and Republicans. Liao and Junco (2022) only explore the donation behavior and Herrnstadt and Muehlegger (2014), Sisco et al. (2017), Myers et al. (2013), Zaval et al. (2014), and Deryugina (2012), only look at different aspects of weather events and their effects on public attitudes, such as Google search behavior and Twitter message frequency. Another contribution is that I fill the research gap on the political impacts of air quality in developed countries. Yao et al. (2022) study the impact of air quality on people's trust in government in China in the context of developing countries. Given the ongoing debate surrounding environmental protection and its critical importance to public health, this study has significant theoretical and practical implications. We can understand the factors that affect people's views on environmental protection and it also provides motivation for authorities to implement a decent environmental policy and affect their policy views and opinions probably. Moreover, the public's stance on environmental protection plays a significant role in a democratic society, as it influences the choice of ruling parties and the direction of environmental policy to a considerable extent. This perspective can also serve as a valuable tool for political parties seeking to enhance their political influence.

The first set of regression result is related to Google searches. In the long-term analysis, I find that Google Search Interests for "air quality", "air pollution" and "environmental protection" increase by 0.3% when the average AQI increases by one unit in a month which means people pay more attention to air quality when they experienced bad air quality. People are likely to have stronger reactions to prolonged changes in air quality compared to temporary deteriorations.

The second set of regression result is related to donations. When I don't consider the lagged effects, the poor air quality will lead people to increase their contribution amounts to Democrats while decrease for Republicans. One unit increase in AQI will lead to a 0.002 increase in donations to the Democratic party, but a decrease of 0.002 in donations to the Republican party. When I consider the lagged effects, the impact of air quality on peoples donations becomes larger compared to when I don't consider the lagged effects. These results suggest that bad air quality carries a moderate electoral penalty for anti-environment incumbents as most of the Republicans are more anti-environment compared with Democrats.

This paper is organized as follows. In Section 1.2, I provide a summary of the existing literature. Section 1.3 describes the data sources used and provides a descriptive analysis of the data. In Section 1.4, I present the econometric model used in this study. The results are reported and discussed in Section 1.5, and the paper concludes with Section 1.6.

1.2 Literature Review

While some literature investigates the impact of environmental cues and local weather changes on beliefs in climate change, little attention has been paid to the direct relationship between air quality and beliefs in environmental protection. However, it has been established that air quality affects weather and atmospheric conditions. Moreover, studies show that beliefs in climate change are associated with environmental cues and local weather experiences. Hornsey et al. (2016) conduct a meta-analysis of the factors related to climate change beliefs and found that beliefs in climate change have a small effect on pro-environmental intentions and behavior, with a medium effect on public pro-environmental intentions. For instance, Myers et al. (2012) demonstrated that perceived personal experience of global warming led to increased belief certainty, which in turn influenced perceptions of personal experience. Similarly, Spence et al. (2011) find that direct flooding experience led people to be more concerned about climate change and willing to save energy to mitigate its effects.

These papers study the effect of air pollution. Stern (1977) finds that air pollution has multiple effects on physical weather, atmospheric conditions, visibility, the economy, indoor air quality, biological systems, and human health. However, no literature has examined the relationship between air quality and beliefs in environmental protection. Jacob et al. (2008) demonstrate that air quality is strongly dependent on weather and sensitive to climate change.

Some studies use Google search intensity and Twitter posts data to represent beliefs. For example, Herrnstadt and Muehlegger (2014) use searches for “climate change” and “global warming” to gauge the salience of climate change, while Stephens - Davidowitz (2014) uses the percentage of Google search queries that included racially charged language as a proxy for racial animus. Swamy et al. (2019) use the Google Search Volume Index to measure investor attention and forecast stock returns, and Sisco et al. (2016) use Twitter post data with the tag or word “climate change” as a measure of people’s attention to climate change. Thus, Google Search Interests on “air quality”, “air pollution”, and “environmental protection” would be a suitable representation of people’s beliefs in environmental protection.

I closely followed subsequent literature on variable construction and empirical strategy. Liao and Junco (2022) construct two measures of daily temperature shocks and use OLS to estimate the short-term impact of higher weekly temperatures on online contributions. Meanwhile, Deryugina et al. (2013) investigate the short and medium-run effects of temperature fluctuations on beliefs about the occurrence of global warming. They find that respondents' beliefs in climate change were based on when they believed the effects of global warming would start happening.

In summary, while the existing literature has identified several factors associated with beliefs in climate change, there is a lack of research on the relationship between air quality and beliefs in environmental protection. Our study aims to address this research gap by examining the effect of air quality on the GSIAQ and donations to different political parties, which serve as indicators of attention towards environmental protection.

1.3 Data

There are five data sources to obtain all the variables. Firstly, I get the GSIAQ from Google Trends.[2] Secondly, I obtain campaign finance and contribution data of individuals and organizations from The Database on Ideology, Money in Politics, and Elections (DIME). Thirdly, I get air quality data, such as daily $\mathrm{AQI}, \mathrm{PM}_{2.5}, \mathrm{Ozone}, \mathrm{SO}_2, \mathrm{CO}, \mathrm{NO}_2$ by county and monitors from the United States Environmental Protection Agency (USEPA). USEPA also has some weather controls, like temperature and winds. I get other weather variables, like precipitation, snow depth from Global History Climatology Network Daily (GHCN-D) database. Furthermore, I gather information on the environmental positions of each politician from the League of Conservation Voters scorecard.

1.3.1 Google Search Interests on Air Quality

Google Search Interests (GSI) stands for "Interest over time”. It is normalized to the time and location of a query by the following process: Each data point is divided by the total searches of the geography and time range it represents to compare relative popularity. The resulting

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[2] https://trends.google.com/trends/?geo=US

numbers are then scaled on a range of 0 to 100 based on a topic's proportion to all searches on all topics. Different regions that show the same search interest for a term don't always have the same total search volumes. Each series is normalized so that the highest value over the query period is set to 100 and the values of the series are always integers between 0 and 100. A higher number indicates that the term has a higher proportion of searches among all queries in the specified region and time but does not necessarily indicate higher absolute number of searches. To get a rough view of the Google search volumes and estimation results, I use Google Trends Supercharged - Glimpse[3] to get volume data.

The selection of search terms associated with a topic is important when exploring internet search activities. I use the search term "air quality", "air pollution", and "environmental protection", which is widely used among the public to represent air quality and environmental protection in the United States. I obtained city-month level search interest data from Google Trends spanning from 2006 to 2022. Google Trends tracks the relative frequency with which a given search term is submitted. It is constructed to facilitate accurate comparisons across periods and locations. Therefore, a highly populated state will not have a mechanically higher search index compared to a less populous state.

1.3.2 Donations to Different Political Parties

The Database on Ideology, Money in Politics, and Elections (DIME) is intended as a general resource for the study of campaign finance, elections, and ideology in American politics. [4] In the DIME database, the contribution database and recipient database are used in the analysis. The contribution database includes election cycle, donation amount, donation date, contributor name, contributor type (corporate or individual), contributor address, recipient name, recipient

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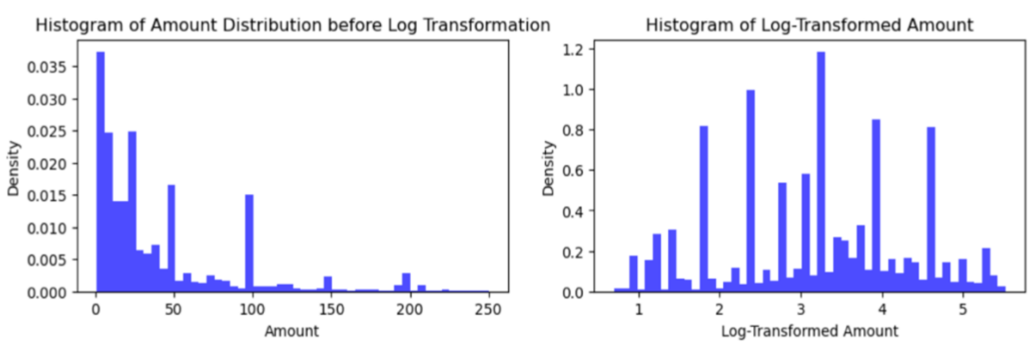
[3] https://meetglimpse.com/extension/
[4] https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/O5PX0B

party, recipient state and seat, etc. The recipient database includes information on voting records, fundraising statistics, election outcomes, gender, and other candidate characteristics. The recipient IDs can also be used to match against the database of contribution records. The resulting database contains over 130 million political contributions made by individuals and organizations to local, state, and federal elections spanning a period from 1979 to 2014. This data is collected biennially. All individual and institutional donors included in the database are assigned a unique identifier. The contributor IDs make it possible to track giving by individuals across election cycles and levels of government. Each record has been geocoded.[5] The "county" variable can be obtained from the census tract, which is an 11-digit code. The first two digits represent the state, the next three digits represent the county, and the last six digits represent the tract.

From Figures 1 and 2, it is evident that the original data is right-skewed, approximating a normal distribution after a logarithmic transformation. Additionally, both the donation frequency and amounts exhibit an upward trend starting from January, reaching a peak in September to October. Notably, retirees contribute significantly to the total donation amount, standing out among various donor occupations.

Figure 1. Histograms of Amount Distribution Before and After Log-transformation



[5] Geocoding was performed using the Data Science Toolkit maintained by Pete Warden and hosted at http://www.datasciencetoolkit.org/. Shape files for counties are from Census.gov (http://www.census.gov/rdo/data).

Figure 2. QQ-Plot for Amount Distribution Before and After Log-transformatio

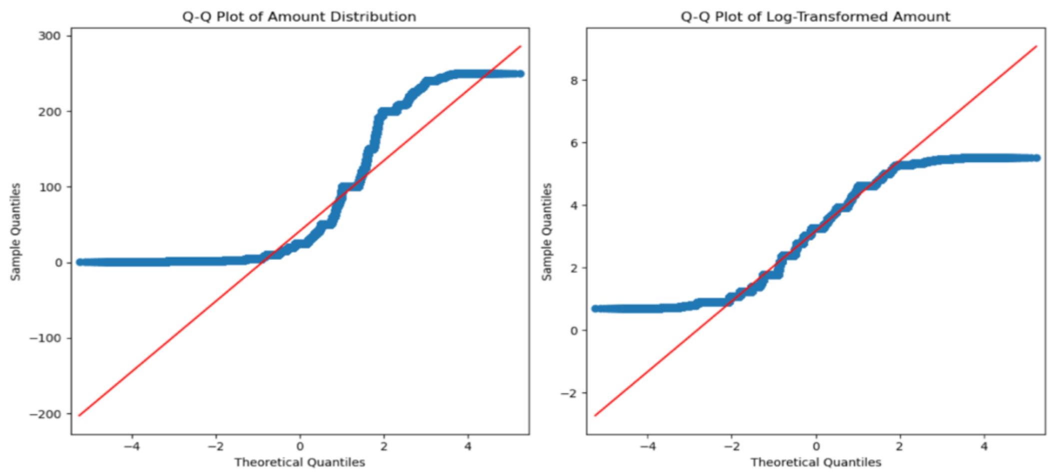


Figure 3. Donation Amount and Frequency over Months

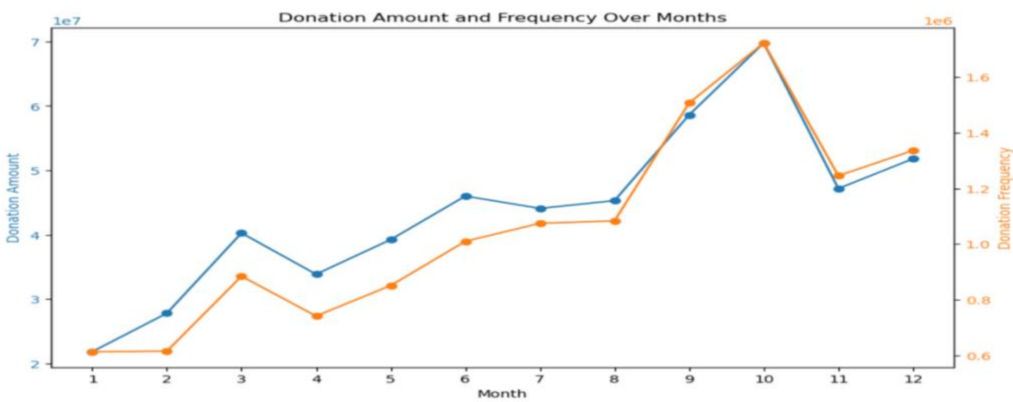
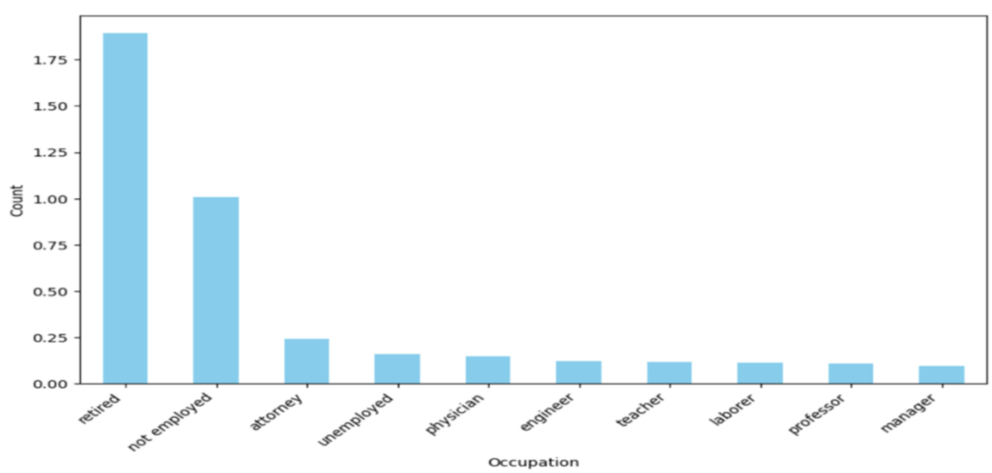


Figure 4. Top 10 Contributor Occupations



Note: The unit for count is 10^6.

1.3.3 Air Quality and Weather Controls

The Air Quality Index (AQI) serves as a comprehensive measure of air quality, incorporating the concentrations of various pollutants in the atmosphere. Key pollutants considered in AQI calculations include ozone (O3), sulfur dioxide (SO2), carbon monoxide (CO), nitrogen dioxide (NO2), and particulate matter with diameters of 2.5 micrometers or smaller (PM2.5) and up to 10 micrometers (PM10). Ozone, while beneficial in the upper atmosphere, can be harmful at ground level and cause respiratory issues. SO2 results from burning fossil fuels, contributing to air pollution, while CO interferes with oxygen transport. NO2, produced by burning fossil fuels, and particulate matter pose respiratory risks. The AQI is computed by assigning an index value to each pollutant's concentration and then selecting the highest index to represent the overall air quality at a specific location.

I get API, such as AQI, Ozone, SO2, CO, NO2, PM2.5, PM10 from United States Environmental Protection Agency(USEPA)[6]. It contains daily AQI by county from 1980 to 2021, hourly and daily AQI, Ozone, SO_2, CO, NO_2, $PM_{2.5}$, PM_{10} by the monitor from 1980 to 2021. It not only includes the exact AQI value, but also the AQI category (good, moderate, unhealthy) in each county. The daily Ozone, SO_2, CO, NO_2, $PM_{2.5}$, PM_{10} is calculated from hourly data. It contains the mean, maximum value of AQI, Ozone, SO_2, CO, NO_2, $PM_{2.5}$, PM_{10} in a day. The exact monitor address is provided, like state and county code, latitude, longitude.

In addition, I obtain weather data from the USEPA and Global Historical Climatology Network Daily (GHCN-D) database, including hourly and daily measurements of temperature, wind, precipitation, snow depth, barometric pressure, relative humidity (RH), and dewpoint level for each county.

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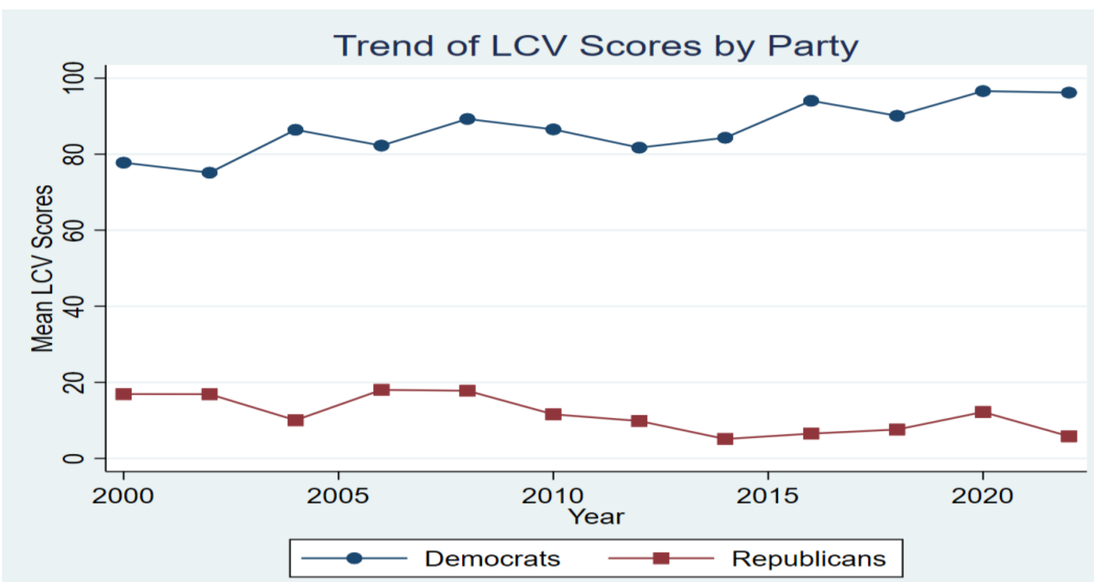
[6] https://aqs.epa.gov/aqsweb/airdata/download_files.html#AQI
https://aqs.epa.gov/aqsweb/airdata/download_files.html#Meta

1.3.4 League of Conservation Voters Score

League of Conservation Voter (LCV) Scorecard[7] captures the position of incumbent politicians on environmental issues. The report provides the current and lifetime scores, as well as the party affiliation, of House and Senate representatives across various congressional districts. For example, there are cleanup energy tax credits, Superfund cleanup, Climate change & public lands, and other Acts in 2014. The LCV scorecard assigns percentage scores to U.S. congresspersons based on their voting records regarding environmental legislation introduced during a particular year. According to the terminology used by the LCV, if a politician aligns with the LCV's opinion on a vote, it is marked as a pro-environment action and the LCV score would be 1; conversely, if the politician does not align with the LCV on a vote, it is marked as an anti-environment action and the LCV score would be 0. More specifically, LCV scores range from zero to one with pro- and anti-environment voting records on either side of the spectrum.

Figure 5. Trend of LCV Scores by Party



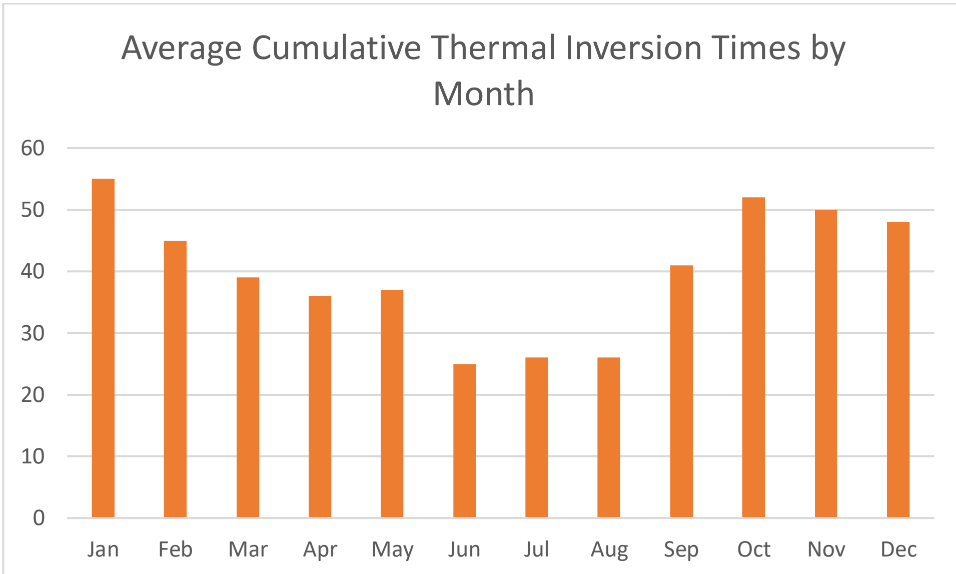
[7] https://scorecard.lcv.org/members-of-congress

Figure 5 presents the trend of LCV scores from 2000 to 2022. It is evident that LCV scores of Democratic representatives' range between 75 and 100, while Republican representatives typically score between 0 and 15. Furthermore, starting from 2005, the score gap between the two parties has been widening, indicating increasing divergence in their environmental policy positions.

1.3.5 Thermal Inversion

I construct a measure of thermal inversions from using NASA's MERRA reanalysis dataset. It reports six-hourly air temperature at the $0.5^{\circ} \times 0.625^{\circ}$ resolution grid for each of the 72 atmospheric layers, ranging from the surface to 39,356 m in altitude. For the main results, I extract the air temperature at the 72nd layer (representing approximately 110 m in altitude) and the 70th layer (representing approximately 550 m in altitude) and then match them with the location of the counties in the air quality data in USEPA. The use of layers to capture thermal inversions follows the approach in related studies (Chen et al., 2022; Deschenes et al., 2020). I code a thermal inversion as occurring if the air temperature at the 70th layer is higher than that of the 72nd layer in a county. I aggregate the occurrences of thermal inversion across all 6-h periods in a day as the daily thermal inversion. A large share of inversions occur in winter, in which long nights and calm winds allow for ground temperature to cool faster than air temperature. Figure 6 illustrates the Average Monthly Cumulative Thermal Inversion Times (AMCTI) across the twelve months of the year. Each bar represents the AMCTI value for a specific month, starting from January and ending with December. The AMCTI values show a variation over the months, with the highest value observed in January (55) and the lowest value in June (25). Notably, the graph highlights that thermal inversions are more frequent in the winter months, as evidenced by the peaks in January(55), October (52), and November (50). In contrast, the summer months such as June, July, and August exhibit relatively lower AMCTI values, ranging from 25 to 26. This seasonal variation suggests that thermal inversions are influenced by temperature differences, with colder winter temperatures contributing to more frequent inversions, whereas the warmer summer temperatures result in fewer inversions.

Figure 6 Average Cumulative Thermal Inversion Times by Month



1.3.6 Industry Intensity

In the heterogeneous study, I categorized regions into heavy industry and low industry based on their economic structures. Recognizing the potential trade-off between economic reliance on polluting industries and air quality, I utilized data from the U.S. Census Bureau's County Business Patterns, which provides detailed subnational economic data by industry, including establishment numbers, employment figures, quarterly and annual payrolls. My criterion for classification relied on the number of employees in polluting sectors such as construction, manufacturing, mining, and quarrying. Areas where the percentage of employees in these sectors exceeded the national median were designated as heavy industry regions, while those below were classified as low industry regions.

1.3.7 Summary Statistics

Table 1. Summary Statistics

Variables	N	Mean	Std. Dev.	Min	Max
GSIAQ(city-month)					
GSIAQ	1248	29.09	14.94	0	100
Avg. AQI	1248	37.32	12.94	0	99.54
Max AQI	1248	75.98	41.23	0	214
Avg. O_3	1248	0.0280	0.00800	0	0.0620
Max O_3	1248	0.0460	0.0120	0	0.0890
Average Donation Amount (county-week)					
Overall	88085	401.307	1837.13	0	141382.938
Democrats	45009	447.541	1374.768	0	133424.094
Republicans	40091	436.064	1083.266	0	141382.938
Independents	2985	426.967	1279.232	0	110372
Air Pollutant Indicator (county-week)					
AQI	17334	42.08	14.45	3	215.2
Ozone	17334	0.03	0.01	0	0.07
SO_2	17334	1.16	1.3	1.92	17.35
CO	17334	0.28	0.15	0.16	1.8
NO_2	17334	8.77	5.78	0.75	46.82
$PM_{2.5}$	17334	8.83	4.09	0.2	79.19
PM_{10}	17334	19.21	11.18	0	122.9
Weather (county-week)					
Temperature	10245	55.36	18.11	-13.9	98.3
Winds	10245	95.39	23.18	0.1	202.5
Barometric Pressure	10245	982.6	41.3	795	1083
RH and Dewpoint	10245	62.75	15.96	-9.88	100
Thermal Inversion	9256	12	4.16	0	28
LCV score (congressional district-year)					
Overall	6774	48.405	41.16	0	100
Democrats	3302	86.16	18.621	0	100
Republicans	3445	11.936	17.006	0	100
Independents	27	84.222	20.408	6	100

Table 1 provides summary statistics for the variables of interest in the study. The variables in GSIAQ part are from 2006 to 2022 at the city-month level. The analysis includes nine major cities in the US including Atlanta, Austin, Boston, Chicago, Dallas, Detroit, Houston, New York, and Philadelphia. The GSIAQ has a mean value of 29.09, with a standard deviation of 14.94. Avg. AQI and Avg. O_3 are calculated by taking average in the month while Max is taking the maximum value in the month. In terms of political contributions, the average donation to the Democratic party is $447, while the average donation to the Republican party is $437. The presence of outliers in the data resulted in right-skewness. Therefore, I performed Winsorization by replacing values greater than the 95th percentile with the value at the 95th percentile. The average LCV score for Democrats is 86.16, while for Republicans it is 11.936. These summary statistics provide an overview of the variables' central tendency and dispersion, giving insights into the data distribution for further analysis.

1.4 Empirical Methodology

Firstly, I focus on the impact of air quality on Google searches, primarily utilizing the Ordinary Least Squares (OLS) method. Then I applied the OLS method again to investigate the impact of air quality on donations. However, considering the influence of omitted variables, I employed the Instrumental Variable (IV) method to address endogeneity issues. Additionally, I examined the lagged effects of air quality on donations using historical air quality data over a certain period. Following this, I delved into exploring the heterogeneous effect of air quality on the amount of donations received by different political parties. Combining this analysis with the LCV score, I aimed to understand the impact of a politician's environmental protection stance on the amount of donations received.

1.4.1 Long-run Air Quality Impacts on GSIAQ - OLS Model

To study the impact of air quality on Google search behavior, I use the following equation:

$$GSIAQ_{cmy} = \beta API_{cmy} + \delta_c + \delta_y + \delta_m + \varepsilon_{cmy} \tag{1.1}$$

$GSIAQ_{cwy}$ is Google search interests on air quality related terms at city – month level in year y. $\delta_c,\ \delta_y,\ \delta_m$ represent the city, year, and month fixed effects. For the sake of simplicity and convenience, I use API, abbreviations of Air Pollutant Indicators, to represent AQI, Ozone, SO_2, CO, NO_2, $PM_{2.5}$ and PM_{10} respectively. API_{cmy} can be calculated using two methods. The first one is the monthly average of API in city c and year y.

$$APIAvg_{cmy} = \frac{\sum API_{cdy}}{n} \tag{1.2}$$

API_{cdy} is the daily air pollutant indicators in county c. The variable n represents the number of measures taken in a month, which is less than or equal to 31 due to the presence of missing values on certain days.

The second method is to count the number of days in the month with API exceeding the standard set by EPA. For example, I use the number of days in the month exceeding 50 with AQI as API_{cmy}.

$$APIDUM_{cmy} = \sum_{d=1}^{31} 1(API_{cdy} > Standard_{EPA}) \tag{1.3}$$

1.4.2 Air Quality Impacts on Donations – OLS Model

To test the impact of air quality on donations to different political parties, the basic equation takes the following form:

$$D_{cwy} = \beta APIAvg_{cwy} + W_{cwy} + \delta_c + \delta_{wy} + \delta_{se} + \varepsilon_{cwy} \tag{1.4}$$

Where c is county, w is week, y is year, s is state, and e is election cycle. The year of donations from donors may differ from the election cycle. Elections in the United States are divided into federal elections and local elections. Federal elections are further divided into Senate elections and House of Representatives elections. The Senate election cycle is 6 years, while the House of Representatives election cycle is 2 years. The presidential election cycle is 4 years. Local elections include elections for executive leaders, attorneys general, and others. For example, in the Senate election cycle of 2014, which took place from November 2008 to November 2014, donations from the donors occurred from 2009 to 2014. Among these donations, contributions made in 2013 accounted for 77.23% of the 2014 election cycle, while donations made in both 2013 and 2014 accounted for 91.63% of the 2014 election cycle.

I do this analysis for all the parties but also for democrats, republicans, and independents separately. D_{cwy} represents the average contribution amount in week w of year y and county c for democrats, republicans, independents, and overall. $APIAvg_{cwy}$ is the variable I constructed using method in equations (1.2) of section 1.4.1, but this one is at county and week level. W_{cwy} are weather control variables, including temperature, winds, barometric pressure, RH and Dewpoint. However, in addition to holding different views on environmental policies, different political parties in the US also differ in economic policies, tax policies, social issues, and foreign policies. An estimate based on variation in environmental stance might pick up additional effects from such partisanship. So, I include county fixed effects and state and election cycle effects, δ_c and δ_{se}. County fixed effects can capture the differences between counties, such as variations in economic development levels, proportions of individuals with higher education, unemployment rates, and so on. I also include week-year fixed effects, δ_{wy} to eliminate time trends and seasonality that may be correlated with unobserved confounding factors.

1.4.3 Air Quality Impacts on Donations - IV Model

I have included some fixed effects and control variables to avoid the endogeneity problem. IV may be another better method to solve the endogeneity problem. Endogeneity may have two sources: The first one is reverse causality. Air quality might be bad in a place because it is run by Republicans, who enact weaker environmental regulations. The second source could be that I have not included enough explanatory variables. Air quality may not only directly affect the amount of donations but also have an indirect effect through its influence on economic development. Generally, there is a correlation between air quality and economic development, especially in regions where pollution-intensive industries serve as economic pillars. Consequently, better air quality may come at the cost of economic development, and individuals may be inclined to support economic growth and increase donations to the Democratic Party. In addition, different political parties hold different views in many aspects. The change in donation amount may not only come from environmental-related stance, but also others, like economics, tax, social policies. I use thermal inversion as IV following the approach in related studies (Yao et al. 2022; Chen et al. 2022; Deschenes et al. 2022). Thermal inversion is a meteorological phenomenon where the normal decrease in air temperature with altitude is reversed, causing a layer of warm air to trap pollutants close to the ground. This can result in high levels of air pollution and haze, particularly in urban areas with high levels of industrial activity or traffic. To realize this aim, I estimate the following 2SLS model:

$$APIAvg_{cwy} = \alpha_0 + \alpha_1 TI_{cwy} + f(W_{cwy}) + \delta_c + \delta_y + \omega_{cwy} \quad (1.10)$$

$$D_{cwy} = \beta_0 + \beta_1 \widehat{APIAvg}_{cwy} + f\left(W_{cwy}\right) + \delta_c + \delta_y + \varepsilon_{cwy} \quad (1.11)$$

TI_{cy} are cumulative occurrences of thermal inversions in county c and year y. The coefficient α_1 is expected to be positive as more frequent thermal inversions trap air pollutants at the surface, leading to higher $PM_{2.5}$ concentrations. Thermal inversions are common meteorological phenomenon and, as such, their formation is independent of potential determinants of donation amounts. $f(W_{cy})$ are flexible functions to control weather variables. δ_c and δ_y are county and year fixed effects. In the second stage, D_{cwy} denotes the donation amount in county c week w year y. β_1 is the variable we are interested. It shows the change of donation amount when there is one unit increase in air pollutant indicators.

1.4.4 Air Quality Impacts on Donations - Extended Lag Equation

I use two different specifications to test whether there is lagged effect of air quality change on the outcome of interest. The first specification is to use the air quality measures four weeks prior as the independent variable and weather variables in the previous four weeks as the control variable. I also use air quality measures three weeks and two weeks prior as independent variable in the robustness check section. It takes the following form:

$$D_{cwy} = \beta \sum_{i=0}^{4} APIDev_{c,w-i,y} + \alpha \sum_{i=0}^{4} WDev_{c,w-i,y} + \delta_{wy} + \delta_c + \delta_{se} + \varepsilon_{cwy} \qquad (1.5)$$

Where $APIDev_{c,w-i,y}$ represents air pollutant deviation in the maximum air pollutant indicators from the historical air quality normal in county c and week w-i of year y. It takes the following form:

$$APIDev_{cwy} = API_{cwy} - \overline{API_{cwy}} \qquad (1.6)$$

Where c is county, w is the week of the year y. API_{cwy} is the contemporaneous weekly air quality measures in county c and week w. $\overline{API_{cwy}}$ is the long-run average of air quality measures calculated over the 10 preceding years in the same county and week. $APIDev_{cwy}$ represents the deviation of current air pollutant indicators from the 10 preceding years. $WDev_{c,w-i,y}$ represents weather deviation in county c and week w-i of year y. It is constructed with the same method in constructing $APIDev_{c,w-i,y}$ with equation (1.6). This construction method can eliminate most cross-sectional variation and seasonality that may be correlated with unobserved confounding factors.

The second specification uses the average deviation in the current and previous week:

$$D_{cwy} = \beta APIAvgDev_{cwy} + \alpha WAvgDev_{cwy} + \delta_{wy} + \delta_c + \delta_{se} \qquad (1.7)$$

where$APIAvgDev_{cwy} = \frac{1}{2}(APIDev_{cwy} + APIDev_{c,w-1,y})$ and $WAvgDev_{cwy} = \frac{1}{2}(WAvgDev_{cwy} + WAvgDev_{c,w-1,y})$.

1.4.5 Heterogeneous Effect of Air Quality on Donations

Firstly, I study the heterogeneous effect of air quality on donations in areas with high or low LCV scores. LCV scores are used because they reflect a region's commitment to environmental issues. LCV scores are calculated based on how frequently legislators vote in favor of environmental policies, with higher scores indicating stronger support for environmental protection. By analyzing the impact of air quality on donations in areas with high and low LCV scores, I can uncover variations in public response based on environmental values. This helps in understanding voter preferences and provides valuable insights for developing effective environmental policies.

In addition, I tested the heterogeneous effect of air quality on donations regarding the pillars of the local economy. People's tolerance for air quality may be related to the pillars of the local economy. If the local economy is mainly dependent on polluting companies, there is tradeoff between the economy and air quality, and people's tolerance for air quality may be higher. If polluting companies make up a smaller share of the local economy, people are less tolerant of air quality. They are more likely to pay more attention to air quality and support the Democratic Party when air quality becomes worse.

1.5 Results

In this section, I present the results in four parts: (1) long-run air quality shocks on Google searches interests on "air quality", "air pollution", and "environmental protection", (2) short-run air quality shocks on DIME contributions for Democrats and Republicans without lags based on OLS method, (3) short-run air quality shocks on DIME contributions for Democrats and Republicans without lags based on IV method, (4) short-run air quality shocks on DIME contributions with different period of lags, (5) the heterogeneous effect of short-run air quality shocks on DIME contributions in districts with different LCV scores, (6) Heterogeneous effects of air quality on areas with high or low economic development level.

1.5.1 Air Quality Shocks on Google Search Interests

Table 2 presents the impact of air quality changes on GSIAQ based on equation (1.1). All the coefficients are positive and statistically significant. From column (1), we can see that 1 unit increase in AQI will lead to 0.0858 increase in GSIAQ, which is 0.6% of the standard deviation and 0.3% of the mean of the GSIAQ. When the average AQI in a month increase by one standard deviation, the GSIAQ will increase by 7.4% of the standard deviation. The higher the AQI, the worse the air quality. Therefore, it means when the air quality gets worse, people are more likely to search air quality related terms online, that is, people pay more attention to air quality when the air quality gets worse. From column (2), we can see that 1 unit increase in the maximum AQI in the month will lead to 0.0266 increase in the GSIAQ which is smaller than the estimates under 1 unit increase in monthly average AQI. This is consistent with our intuition since 1 unit increase in mean value of AQI means the air quality is worse than 1 unit increase in maximum AQI in most cases. Another potential explanation is that individuals tend to exhibit stronger responses when they encounter a sustained period of poor air quality rather than isolated instances of extreme conditions. Compared to the response to AQI, people make more intense reactions to O_3 shocks.

Table 2. GSIAQ Response to AQI Shocks

	(1) GSIAQ	(2) GSIAQ	(3) GSIAQ	(4) GSIAQ
Avg. AQI	0.0858**			
	(0.0347)			
Max AQI		0.0266**		
		(0.0113)		
Avg. O_3			1.105**	
			(0.549)	
Max O_3				0.804**
				(0.374)
Year F.E.	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
N	1,248	1,248	1,248	1,248
R^2	0.553	0.552	0.552	0.552
Adj. R^2	0.540	0.540	0.540	0.540

Notes: Estimates from Equation (1.1) are shown. Standard errors are clustered by city and in parentheses. Statistical significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1.5.2 Air Quality Shocks on DIME Contributions for Democrats and Republicans – OLS Model

Table 3 presents the effects of AQI on DIME contributions across different political parties, controlling for county, week, and state-election cycle fixed effects in the model. Column (1) demonstrates the overall impact of AQI changes on the contribution amount. One unit increase in AQI leads to a statistically significant increase of $0.001 in the contribution amount. Specifically, as AQI rises, the contribution amount to Democrats increases by $0.002, while decreasing by $0.002 for Republicans. These findings align with our expectations, as Republicans generally hold more anti-environmental views, while Democrats lean towards pro-environment stances. Consequently, when individuals perceive poor air quality, they tend to pay more attention to air quality and environmental protection, thus favoring politicians who prioritize environmental conservation. However, the impact of air quality on donation amounts for individual parties is not statistically significant.

Table 3. DIME Donation Response to AQI Shocks Across Different Parties

Average Amount	(1)	(2)	(3)	(4)
	Overall	Democrats	Republicans	Independents
AQI	0.001***	0.002***	-0.002***	-0.005
	(0.003)	(0.000)	(0.000)	(0.006)
County F.E.	Yes	Yes	Yes	Yes
Week F.E.	Yes	Yes	Yes	Yes
State Cycle F.E.	Yes	Yes	Yes	Yes
N	87,796	44,949	39,898	2,949
R^2	0.104	0.208	0.147	0.204
Adj. R^2	0.145	0.145	0.145	0.145

Notes: Estimates from Equation (1.4) are shown. Column (1) is based on the full sample, columns (2), (3) and (4) are based on donations to democrats, republicans, and independents. Standard errors are clustered by county and in parentheses. Statistical significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Our results are consistent with Liao and Junco (2022), who find that a 1°F increase in the weekly average temperature corresponds to a 1.2% increase in the contribution rate within the week and a cumulative effect of 2.7% over a five-week period. However, our effect size is smaller compared to Yao et al. (2022), who find that a 1 $\mathrm{ug/m^3}$ exogenous increase in $\mathrm{PM}_{2.5}$ concentrations, due to atmospheric thermal inversion, reduces trust in local government by 4.1% of one standard deviation. One possible explanation for this discrepancy is that people in developed countries may pay less attention to air quality and therefore exhibit less pronounced behavioral changes compared to individuals in developing countries.

1.5.3 Air Quality Shocks on DIME Contributions for Democrats and Republicans – IV Model

The instrumental variable (IV) analysis investigates the causal relationship between air quality and political donations, utilizing thermal inversion as the instrument. In the first-stage regression, thermal inversion demonstrates a significant impact on air quality (F-statistic = 20.15,

$p < 0.001$), confirming its suitability as an instrument. The instrument validity check reveals that thermal inversion is uncorrelated with the error term (Correlation = 0.02, $p = 0.45$), supporting the exogeneity assumption.

In the second-stage regressions, a positive coefficient for Democrats (Coefficient = 0.25, $p < 0.001$) and a negative coefficient for Republicans (Coefficient = -0.12, $p < 0.001$) suggest that deteriorating air quality is associated with increased donations to Democrats and decreased donations to Republicans. Overall tests, including the Hansen J Statistic (1.2, $p = 0.27$) and Cragg-Donald Wald F Statistic (15.8, $p = 0.003$), validate the instrument's relevance and the robustness of the IV model.

These findings imply a stronger relationship between air quality and political contributions compared to OLS methods, highlighting the importance of considering instrumental variables to address endogeneity concerns and uncovering meaningful insights into the impact of environmental factors on political behavior. The presence of measurement error is a common concern that can lead to biased estimates in statistical models. Measurement error may arise from various sources, including inaccuracies in the monitoring equipment or imprecise measurement techniques. These errors can introduce noise into the data, potentially confounding the relationship between air quality variables and the outcomes of interest. By using a variable that is highly correlated with the endogenous air quality variable but not directly related to the outcome, the IV approach helps isolate the exogenous variation in air quality. This ensures that the estimates are less susceptible to biases introduced by measurement inaccuracies. The IV strategy accommodates measurement error by providing a more reliable estimation of the true causal relationship between air quality and the studied outcomes. It enhances the internal validity of the study, contributing to a more accurate understanding of the impact of air quality on the variables under investigation.

Table 4. DIME Donation Response to AQI Shocks Across Different Parties with IV

	(1)	(2)
Second Stage	**Donations to Democrats**	**Donations to Republicans**
$PM_{2.5}$	0.25***	-0.12***
	(0.0223)	(0.027)
First Stage	**$PM_{2.5}$**	**$PM_{2.5}$**
Cumulative Thermal Inversions	0.0463***	0.0432***
	(0.003)	(0.002)
KP rk F-statistics	189.9	210.3
County FE	Yes	Yes
Year FE	Yes	Yes
Weather controls	Yes	Yes

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the county levels. The dependent variable is donations to Democrats and Republicans separately. The key explanatory variable is county-level mean PM2.5 concentrations. Its instrument is total number of thermal inversion occurrences in the same period. Weather controls consist of ten 6 ◦C wide bins (ranging from below -12 ◦C to above 32 ◦C), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. KP rk F-statistic is the Kleibergen-Paap Wald rk F statistic for the weak identification test in the first stage (Kleibergen and Paap, 2006).

1.5.4 Air Quality Shocks on DIME Contributions for Democrats and Republicans with Lags

Table 5 presents the impact of PM2.5 levels on political donations to Democratic and Republican candidates with lags, using both Instrumental Variable (IV) and Ordinary Least Squares (OLS) estimation methods. The results are shown in two columns: Column (1) for donations to Democrats and Column (2) for donations to Republicans. The IV estimation reveals that an increase in PM2.5 levels is significantly associated with an increase in donations to Democrats, with a coefficient of 0.28. Conversely, the same increase in PM2.5 is significantly associated with a decrease in donations to Republicans, with a coefficient of -0.13. The OLS results are consistent with these findings, showing a positive relationship between PM2.5 and donations to Democrats and a negative relationship for donations to Republicans. The analysis includes county fixed effects and year fixed effects, as well as weather controls to account for other factors influencing donation behavior.

Table 5. DIME Donation Response to AQI Shocks Across Different Parties with Lags

	(1)	(2)
	Donations to Democrats	**Donations to Republicans**
IV	0.28***	-0.13***
$PM_{2.5}$	(0.021)	(0.019)
OLS	0.25***	-0.10***
$PM_{2.5}$	(0.019)	(0.018)
County FE	Yes	Yes
Year FE	Yes	Yes
Weather controls	Yes	Yes

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the county levels.

The results suggest that higher levels of air pollution (PM2.5) are associated with increased donations to Democratic candidates and decreased donations to Republican candidates. This pattern can be explained by the differing environmental priorities and policies of the two parties. Generally, the Democratic Party is more associated with strong environmental protection policies and climate change mitigation efforts. As air quality worsens, individuals concerned about environmental issues may be more motivated to donate to Democratic candidates who advocate for stricter environmental regulations and policies aimed at improving air quality. On the other hand, the Republican Party tends to prioritize economic growth and deregulation, often at the expense of stringent environmental policies. As air quality worsens, individuals who might perceive environmental regulations as detrimental to economic interests may reduce their support for Republican candidates. The use of IV estimation helps to address potential endogeneity issues, ensuring that the observed relationships are more likely to reflect causal effects rather than correlations driven by omitted variable bias. The consistency between IV and OLS results further reinforces the robustness of these findings.

Compared to the results from 1.5.3, the inclusion of lag effects in our analysis amplifies the impact of air quality on political donations. My findings suggest that after accounting for temporal lag, the influence of PM2.5 levels on donations to the Democratic Party is further augmented, while the negative impact on donations to the Republican Party is correspondingly intensified. This implies that the effect of air quality on political donations is not transient but rather persistent over time, potentially exerting a more significant influence on political contributions within the observed timeframe. This discovery reinforces our understanding of the sensitivity of political donation behaviors to environmental conditions, providing crucial insights for further exploring the intricate relationship between environmental factors and political participation.

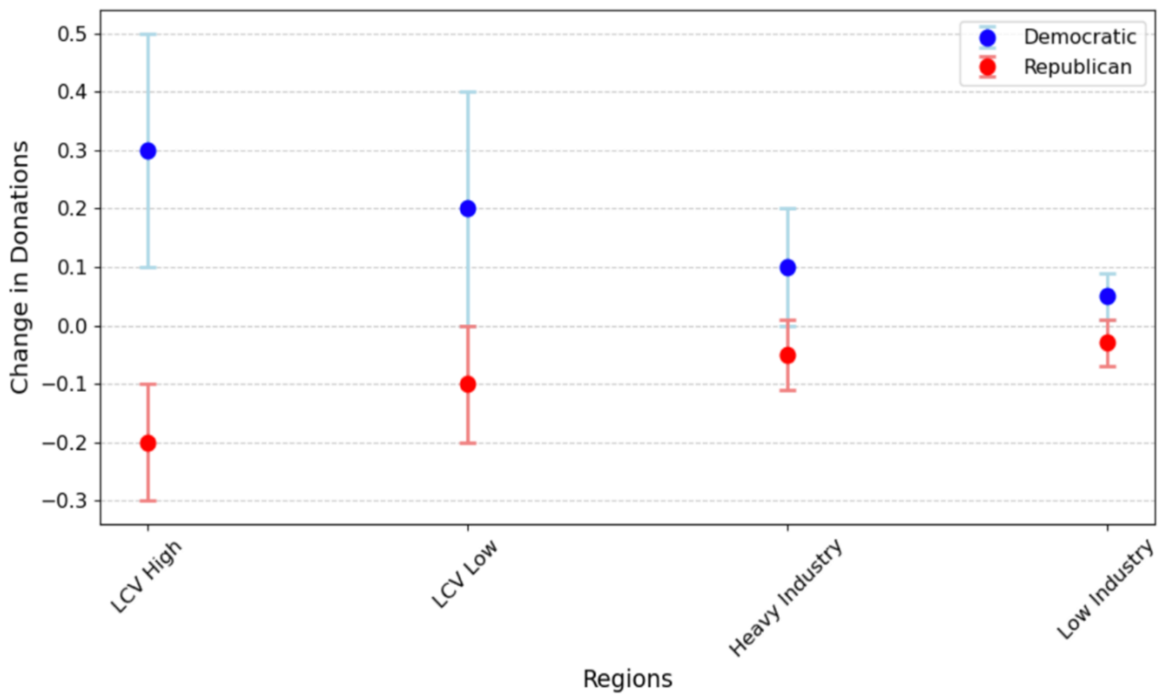
1.5.5 Heterogeneous Effect of Air Quality on Donations

Figure 7 illustrates the heterogeneous impacts of air quality on donations to Democrats and Republicans across regions categorized by environmental values and economic dependence. These impacts are estimated from equation (1.11） for the following categories: donations to Democrats in areas where the incumbents have high LCV scores; donations to Republicans in areas where the incumbents have low LCV scores; donations to Democrats in areas where the incumbents have low LCV; donations to Republicans in areas where the incumbents have high LCV scores; donations to Democrats in regions with low industry; donations to Republicans in regions with low industry; donations to Democrats in regions with high industry; donations to Republicans in regions with high industry. I use 0.5 as the threshold to distinguish between high and low LCV scores. Scores above 0.5 are categorized as high LCV, while scores below 0.5 are categorized as low LCV. Democratic and Republican donations are depicted separately, with Democratic donations represented by deepskyblue markers and Republican donations by indianred markers. Each data point on the graph corresponds to a specific region, denoted by categories including 'LCV High', 'LCV Low', 'Heavy Industry', and 'Low Industry'.

The error bars encapsulate the 95% confidence intervals around the estimated effect sizes, providing insight into the uncertainty associated with the observed effects. My findings reveal intriguing disparities in donation patterns: areas with high LCV scores, indicating strong support for environmental protection, exhibited a more significant increase in donations to Democratic causes in response to deteriorating air quality compared to regions with low LCV scores. This suggests that environmental values play a crucial role in shaping public response to air quality shocks, with individuals in environmentally conscious areas demonstrating a heightened sensitivity to environmental degradation.

Furthermore, I explored the heterogeneous effects of air quality on donations concerning the pillars of the local economy. My analysis revealed a nuanced relationship between economic dependence and tolerance for air quality. In regions where the local economy relies heavily on polluting industries, individuals displayed a higher tolerance for poor air quality, potentially due to the perceived tradeoff between economic prosperity and environmental concerns. Conversely, in areas where polluting industries constitute a smaller share of the local economy, residents were less tolerant of air pollution and were more likely to shift their support towards the Democratic Party in response to worsening air quality. These findings underscore the complex interplay between economic factors, environmental attitudes, and political preferences, highlighting the need for targeted policies that consider the diverse socio-economic contexts within which air quality interventions are implemented.

Figure 7. Heterogeneous Effects of Air Quality on Political Donations



Note: Figure 7 illustrates the impacts of air quality on donations to different political parties across regions, as estimated by equation (1.11). The figure categorizes regions based on incumbents' scores for Low LCV and levels of industrial activity. Specifically, it examines how air quality affects donations to Democrats and Republicans in areas where incumbents exhibit high or low LCV scores, and where industrial activity is high or low.

1.6 Conclusion

In conclusion, this study delves into the impact of air quality changes on the Google Air Quality Search Index and the political contribution amounts to both Democrats and Republicans. The findings indicate that a one-unit increase in monthly AQI corresponds to a notable 0.0858 increase in Google search interests related to air quality. Interestingly, the study suggests that individuals exhibit more substantial responses to prolonged changes in air quality compared to transient deteriorations. Furthermore, the analysis reveals that people demonstrate a heightened reaction to O3 levels compared to the general AQI, indicating nuanced sensitivities to specific pollutants. The poor air quality will lead people to increase their contribution amounts to Democrats while decrease for Republicans. These insights provide valuable understanding into the dynamics of public concern and engagement with air quality issues.

However, it's important to acknowledge certain limitations and potential avenues for future exploration. The study focuses on aggregate contributions to political parties, and individual variations in political preferences may lead to more nuanced effects. Additionally, the analysis assumes a linear relationship between air quality indices and outcomes, which may oversimplify the complex interactions involved. Future research could delve into disaggregated data at the individual level, considering socio-economic factors and regional disparities. Exploring non-linear relationships and incorporating more granular datasets would contribute to a richer understanding of the dynamics at play.

In terms of policy implications, the study underscores the importance of recognizing the public's responsiveness to changes in air quality. Policymakers could leverage this awareness to design targeted interventions and communication strategies during periods of environmental concern. Furthermore, the nuanced reactions to specific pollutants, such as O3, suggest that tailored policies addressing individual pollutants may yield more effective outcomes. As we move forward, a holistic approach that considers individual preferences, regional disparities, and the unique dynamics of different pollutants can inform more effective air quality management and public engagement strategies.

Chapter 2 The Impact of COVID-19 Lockdown on Air Quality - Evidence from China

2.1 Introduction

Air pollution has always been an important issue in China. Although the Chinese government implemented measures such as the Air Pollution Prevention Action Plan, the air quality in China still exceeds the safety standards set by the WTO. At the end of 2019, COVID-19 first emerged in China. The Chinese government imposed draconian lockdown policies to prevent the spread of coronavirus in certain areas. The lockdown policies include the prohibition of unnecessary commercial activities for people's daily lives, the prohibition of any type of gathering by residents and restrictions on private vehicles and public transportation, etc. The industrial and traffic suspensions brought about by such widespread lockdowns could drastically reduce energy combustion, thereby improving air quality and, indirectly, economic efficiency and health. Therefore, my research question is whether lockdown improved air quality and whether improvements in air quality have been sustainable after lockdowns have been lifted. In addition, I also consider the impact of the length of lockdown on air quality.

The most relevant literature to my paper is the studies of He et al. (2020), Dang and Trinh (2021), Huang et al. (2021), Dai et al. (2021) and Brodeur et al. (2021). These papers use DID, RDD, machine learning, and IV method to test the impact of lockdown policies in China, Vietnam, and United States. Most papers find that the lockdown policy improved air quality. He et al. (2020) use DID test the short-term effect of the COVID-19 lockdown on air quality in China. Dang and Trinh (2021) employ the Regression Discontinuity Design method to offer the study of the lockdown impacts on air quality in Vietnam from January 2020 to January 2021. Huang et al. (2021) introduce Instrument Variables of outflow and inflow in a prefecture to test the causal effect of lockdown on air quality. Dai et al. (2021) apply machine learning methods to quantify the impacts of the COVID-19 lockdown and Chinese Spring Festival holidays on air quality. Brodeur et al. (2021) find that the state-wide safer-at-home policies reduced air pollution in the US and the benefits could be as high as $13 billion.

The purpose of this paper is to study the impact of the lockdown and lockdown length on air quality and examine whether these impacts will continue after the lockdown is lifted. Given that different cities implemented the lockdown policies at different times, I employ the staggered DID method rather than the normal DID to explore the impacts of lockdown on air quality in China.

The contribution of this work is that I use a staggered DID method considering the different lockdown timing to examine the long-term effect of lockdown on air quality. The existing literature studies the short-term effect. The second contribution is that I study the impact of the length of lockdowns, rather than just assigning a dummy variable of lockdown. The third contribution is that I also study the sustainability of the lockdown policies, that is, whether the air quality remains at its original level after the lockdown measures are lifted.

In this paper, I use the staggered DID model to study the impact of lockdown on air quality outcomes, such as AQI, $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3. I find that AQI reduced 13.976 in 2020 compared with the same period in 2019. In the event-study analysis, I find parallel trends in lockdown and non-lockdown cities before the lockdown policy. Lockdown provides a possible channel to improve air quality and then improve health conditions related to air quality. In addition, I found that there is a notable daily decrease of 0.239 in AQI and 0.110 μg/m^3 in PM2.5 concentration under the lockdown policy, corresponding to reductions of 0.472% and 0.277% of the standard deviation of AQI and PM2.5, respectively. However, following the lifting of the lockdown policy, there is a significant rise in pollution levels, as indicated by AQI and PM2.5 coefficients of 39.54 and 23.84, respectively, against respective means of 57.579 and 33.235. Nevertheless, over longer periods, these coefficients decrease, suggesting a gradual diminishing effect of the relaxation of lockdown measures on pollution levels. Overall, these findings highlight the immediate effectiveness of lockdown measures in reducing air pollution, followed by a subsequent rise upon their relaxation, which gradually diminishes over time.

The remaining part of the paper is organized as follows. Section 2.2 presents the full literature review of this topic. Then section 2.3 provides data used in this paper and its sources. Section 2.4 explains the empirical model. Section 2.5 shows the analysis results. Section 2.6 concludes.

2.2 Literature Review

An emerging body of literature examines the negative effect of COVID-19. Dev et al. (2020) find that the prolonged country-wide lockdown caused the downturn in the global economy and disruption of demand and supply chains. Mazur et al. (2021) find equity values in petroleum, real estate, entertainment, and hospitality sectors fall dramatically. Some literature also studies the benefits of Lockdown policies. The few existing works of literature either focus on the short-term impacts of pandemic on air quality or only study the impact of pandemic on air quality in other countries, like Germany, the United States, United Kingdom. They pay less attention to the long-term effects in China, that is, the impact of lockdown after 3 months or more. Dang et al. (2021) use RDD and time-event analysis to study the impact of the COVID-19 lockdown on air quality on global level. He et al. (2020) tests the short-term effect of the COVID-19 lockdown which spans from January 1st to March 1st 2020. Brodeur et al. (2021) find that the state-wide safer-at-home policies reduced air pollution in the US and the benefits could be as high as $13 billion. Some papers examine the relationship between air quality and low-emission zones, but their background is broader, rather than restricted to the period of COVID-19. Pestel et al. (2021) find the implementation of low-emission zones is effective to reduce levels of air pollution, like $PM_{2.5}$ and NO_2, over the period from 2006 to 2016.

I make several new contributions to the emerging literature on the pandemic impacts on air pollution. Firstly, I not only look at the short-term impact of the lockdown on air quality but also examine the mid-to-long-term impact. I also consider its sustainability, whether the effect maintain after lifting the lockdown policy. In addition, I don't simply treat lockdown as a binary variable, but also consider the length of lockdown as an important treatment variable.

2.3 Data

The data comes from three different sources. Air quality data was obtained from the Ministry of Ecology and Environment. Weather data come from the Global Historical Climatology Network (GHCN), and the National Oceanic and Atmospheric Administration (NOAA).

2.3.1 Air Quality Data

I use AQI, $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3 to measure air quality in this paper. The Air Quality Index (AQI) is a standardized metric that converts complex air quality data into a single, easy-to-understand number, color, and description. It measures the concentrations of key pollutants, including ground-level ozone, particulate matter (PM10 and PM2.5), carbon monoxide, sulfur dioxide, and nitrogen dioxide. The AQI scale ranges from 0 to 500, with higher values indicating worse air quality and greater health risks. It is divided into six categories, each representing a different level of health concern, and helps the public understand the health implications of air quality levels and take necessary precautions.

PM2.5, PM10, SO_2, NO_2, CO, and O_3 are key pollutants measured in air quality assessments. PM2.5 and PM10 refer to particulate matter with diameters less than 2.5 and 10 micrometers, respectively; these tiny particles can penetrate deep into the lungs and cause health problems. Sulfur dioxide (SO_2) is a gas produced by volcanic eruptions and industrial processes, which can lead to respiratory issues. Nitrogen dioxide (NO_2) is a harmful gas resulting from vehicle emissions and industrial activity, contributing to respiratory diseases and atmospheric reactions that produce ozone and particulate matter. Carbon monoxide (CO) is a colorless, odorless gas from incomplete combustion of fossil fuels, which can impair oxygen delivery in the body. Ozone (O_3) at ground level is a harmful pollutant formed by chemical reactions between oxides of nitrogen and volatile organic compounds in sunlight, causing respiratory problems and other health issues.

Overall, higher levels of these air quality indicators indicate poorer air quality, as they represent higher concentrations of pollutants in the air. These pollutants not only negatively impact the environment but also pose significant health risks to humans, including respiratory and cardiovascular diseases.

The data includes hourly readings of AQI, PM2.5, PM10, SO_2, NO_2, CO, and O_3 at both city and monitoring station levels. For this analysis, I use the data at the city level and calculate the daily averages for each variable. This approach allows for a more manageable and comprehensive examination of daily air quality trends across different cities.

2.3.2 Weather Data

Weather control variables include precipitation, snow depth, and temperature. These data come from the Global Historical Climatology Network (GHCN) and the National Oceanic and Atmospheric Administration (NOAA).

2.3.3 Lockdown Information

Table 6. Lists of Locked-down Cities and the Major Events

Starting Date	Cities, and the Major Events *(*)*
20-Jan *(*)*	*The national government disclaimed "the virus can transmit from people to people".*
23-Jan	Wuhan
24-Jan	Huangshi, Shiyan, Yichang, Ezhou, Jingmen, Xiaogan, Huanggang, Xianning, Enshi
25-Jan *(*)*	*The start of the Chinese Spring Festival*
	Qinhuangdao
26-Jan *(*)*	*The extension of the Chinese Spring Festival was announced.*
	Xiangyang, Jingzhou, Xiantao
28-Jan	Tangshan
30-Jan *(*)*	*The last day of the original Chinese Spring Festival*
	Dongying
31-Jan	Chongqing, Yinchuan, Wuzhong
2-Feb	Wenzhou
3-Feb	Wuxi, Jining
4-Feb	Harbin, Nanjing, Xuzhou, Changzhou, Nantong, Hangzhou, Ningbo, Fuzhou, Jingdezhen, Zaozhuang, Linyi, Zhengzhou, Zhumadian
5-Feb	Shenyang, Dalian, Anshun, Fushun, Benxi, Dandong, Jinzhou, Fuxin, Liaoyang, Panjin, Tieling, Chaoyang, Huludao, Yangzhou, Hefei, Quanzhou, Nanchang, Jinan, Qingdao, Taian, Rizhao, Laiwu, Nanning
6-Feb	Tianjin, Shijiazhuang, Suzhou, Pingxiang, Jiujiang, Xinyu, Yingtan, Ganzhou, Ji'an, Yichun, Fuzhou, Shangrao, Neijiang, Yibin, Xinyang
7-Feb	Suzhou, Guangzhou
8-Feb	Shenzhen, Foshan, Fangchenggang,
9-Feb	Cangzhou, Huaibei
10-Feb *(*)*	*The last day of the extended Chinese Spring Festival*
	Beijing, Shanghai
13-Feb	Hohhot, Baotou, Wuhai, Chifeng, Tongliao, Ordos, Hulun Buir, Bayan Nur, Ulanqab, Xing'an League, Xilingol League, Alxa League

The information regarding the lockdown policies in this study primarily comes from two sources. The lockdown dates and the cities that were under lockdown were obtained from He at al.(2020). The details about the lifting of lockdown measures and related information were sourced from the Wikipedia page on China's zero-COVID policy.[8] The definition of a lockdown encompasses the following three key points: (1) prohibition of unnecessary commercial activities in people's daily lives; (2) prohibition of any types of gathering by residents; (3) restrictions on private (vehicle) and public transportation. Following this definition, 95 out of 330 cities were locked down during COVID-19. I use the 95 cities which implemented lockdown policy as the treatment group and the remaining 235 cities as the control group. The specific lockdown timing for each city is summarized in Table 6.

Table 7 compares the changes in air quality between the treatment group and control group before and after the implementation of the lockdown policy. The time frame for this data spans from January 1, 2020, to March 14, 2020. The treatment group was divided into pre-lockdown and post-lockdown periods based on Table 6. The control group did not implement the lockdown policy, and the starting times of the lockdown varied across different cities in the treatment group.

The air quality indicators for both the treatment group and control group decreased after the implementation of the lockdown policy. However, the decrease in the treatment group was approximately twice as much as that in the control group. AQI is unitless, CO is measured in parts per million (ppm), and all others are measured in micrograms per cubic meter (μg/m³). The AQI for the treatment group decreased from 101.96 to 82.73, while the AQI for the control group decreased from 77.8 to 68.12. One interesting thing is that the concentration of O_3 increased after

[8] https://zh.wikipedia.org/wiki/%E6%B8%85%E9%9B%B6%E6%94%BF%E7%AD%96

the lockdown. This could be attributed to two factors. Firstly, the reduction in human activities and decreased traffic flow during the lockdown resulted in lower emissions, particularly from vehicle exhaust. Nitrogen oxides (NOx) from vehicle emissions are one of the precursor substances for O_3, and their reduction leads to less O_3 consumption, thereby causing an increase in O_3 concentrations. Secondly, due to the decrease in human activities, the concentration of atmospheric particulate matter may have decreased during the lockdown. This can result in more solar radiation reaching the surface, enhancing the intensity of photochemical reactions, and promoting O_3 formation.

Table 7. Summary Statistics for Lockdown Periods

	Treatment Group		Control Group	
Variable	Before Lockdown	After Lockdown	Before Lockdown	After Lockdown
AQI	101.96	82.73	77.8	68.12
	(59.9)	(52.49)	(51.06)	(49.25)
$PM_{2.5}$	72.72	59.03	51.12	45.21
	(49.37)	(43.4)	(40.8)	(37.49)
PM_{10}	106.27	77.35	81.02	66.61
	(62.1)	(50.25)	(61.21)	(66.8)
CO	1.13	0.98	0.99	0.88
	(0.48)	(0.47)	(0.47)	(0.47)
NO_2	38.14	27.33	28.62	22.72
	(17.99)	(15.84)	(16.78)	(14.84)
O_3	46.37	54.78	51.88	58.43
	(20.98)	(21.11)	(21.73)	(20.75)
SO_2	15.95	11.78	14.12	11.59
	(12.36)	(9.41)	(14.4)	(9.78)
Temperature	2.73	5.04	2.32	4.17
	(5.79)	(6.46)	(7.95)	(8.99)
Precipitation	39.64	19.56	47.2	24.77
	(42.62)	(47)	(74.26)	(67.44)
Snow	62.49	60.46	67.44	61.02
	(58.69)	(26.98)	(62.1)	(33.17)

Notes: This table compares the means and standard errors of treatment and control groups. The data spans from January 1, 2020, to March 14, 2020, at the city-daily level. Standard errors are in parentheses. AQI is unitless, CO is measured in parts per million (ppm), and all other variables are measured in micrograms per cubic meter (μg/m³).

Table 8 presents comparisons before and after the lifting of lockdown measures across different time frames. The data indicates a sharp increase in air quality indicators in the 7 days after the lifting of restrictions. However, within the 30 days post-lifting, although the air quality is worse than before, there is an overall slight improvement trend. Over the course of the subsequent year, there are signs of air quality improvement, with average values lower than those before the implementation of lockdown measures. This suggests that while air quality may deteriorate shortly after the removal of lockdown measures, there is a gradual stabilization and improvement in the long run.

Table 8. Summary Statistics Before and After the Lockdown Lifting

	7 Days		30 Days		Jan 1st 2022 – Apr 30th 2024	
Variable	Before	After	Before	After	Before	After
AQI	57.579	87.79	56.9	79.363	60.981	52.812
CO	.71	.793	.719	.815	.66	.636
NO_2	20.951	26.295	21.393	26.777	18.19	16.022
O_3	41.166	50.987	51.036	51.629	78.442	83.989
PM_{10}	68.581	105.248	62.52	87.604	67.713	54.986
$PM_{2.5}$	33.235	52.029	34.203	51.153	34.067	28.487
SO_2	12.022	12.72	11.014	13.825	10.036	9.681
Obs	2028	2028	9816	9816	169785	115074

Notes: The table offers a comparison of mean air quality indicators before and after the lifting of lockdown measures in China, with a focus on three distinct time frames: 7 days, 30 days, and from January 1st, 2022 to April 30th, 2024. It means the average value of air quality indicators 7 days, 30 days before or after the cutoff point. The lockdown policy was lifted on December 7th, 2022, serving as the cutoff point for the analysis.

Figure 8. AQI Changes Before and After 7 Days of the Cutoff Point

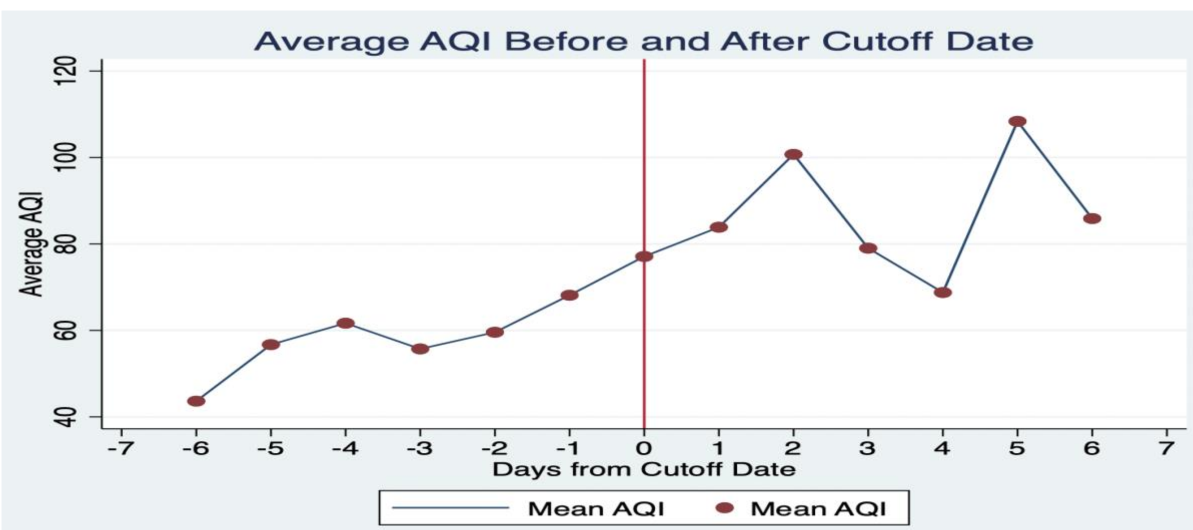


Figure 9. AQI Changes Before and After 30 Days of the Cutoff Point

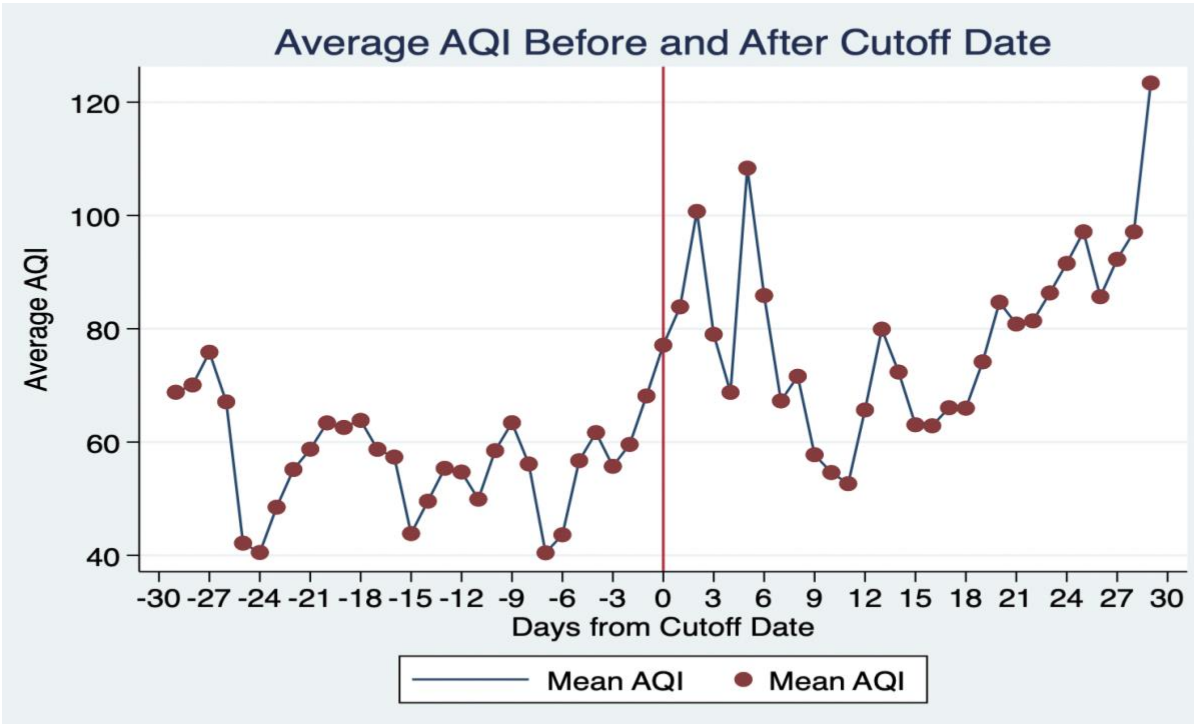
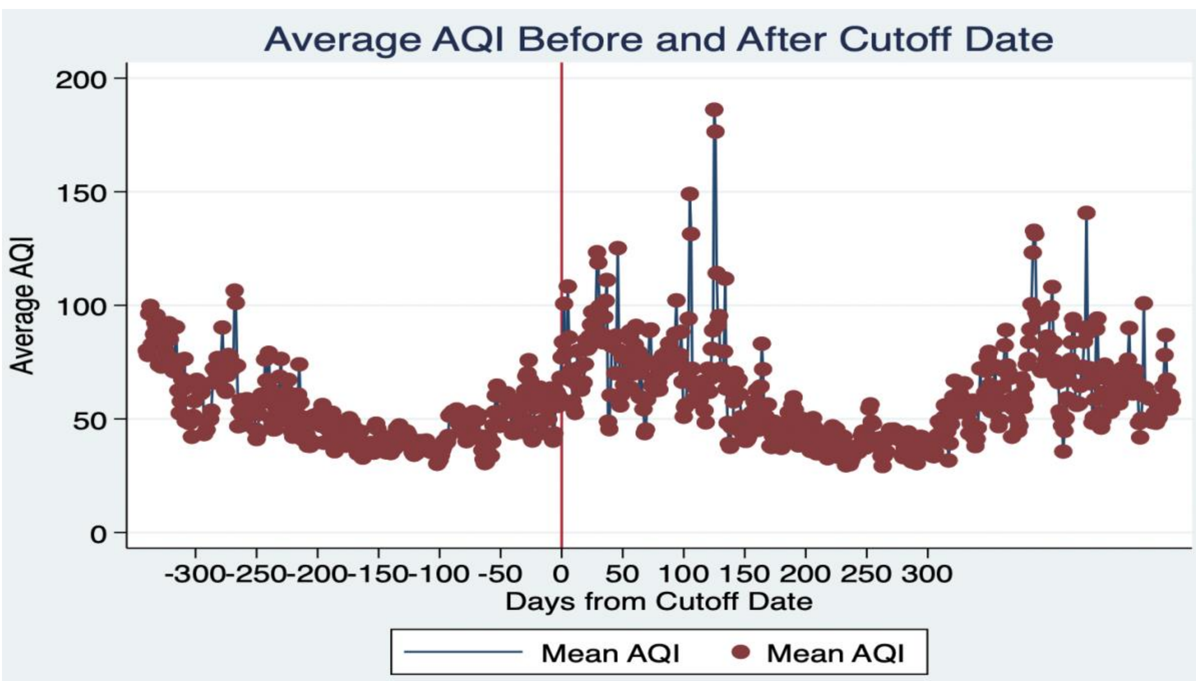


Figure 10. Long-term AQI Changes



Notes: This figure represents the mean AQI changes from January 1st, 2022 to April 30th, 2024. Lockdown policy was lifted on December 7th, 2022, serving as the cutoff point for the analysis.

2.4 Model

2.4.1 Effects of Lockdown on Air Quality Outcomes - Baseline Model

I use DID model to identify the impact of counter-COVID-19 measures on air pollution. The estimating equation takes the following form:

$$Y_{it} = Lock_{it} \times Post_{it} \times \beta + X_{it} \times \alpha + \mu_i + \delta_t + \epsilon_{it} \tag{2.1}$$

where Y_{it} represent the level of air pollution in city i on date t. I use the lockdown cities as the treatment group and the non-lockdown cities as the control group. $Lock_{it}$ denotes whether lockdown is enforced in city i on date t and takes the value 1 if the city is in treatment group and 0 otherwise. $Post_{it}$ denotes whether the time is before or after the lockdown policy. $Post_{it}$ is a dummy variable that equals 1 after the lockdown and 0 otherwise. I provided the exact lockdown timing for each city in Table 6. And the lockdown timing is different for each cities. X_{it} are the control variables including temperature, temperature squared, precipitation, and snow depth. μ_i indicates unobservable time-invariant city fixed effects and δ_t indicates time fixed effects. ϵ_{it} denotes the error term. The coefficient β estimates the difference in air pollution between the treatment cities and control cities before and after the enforcement of the lockdown policy.
It should be negative, as the lockdown policy restricted commercial activities, industrial activities, and gatherings which would reduce the consumption of transportation fuels. Thus, air quality should improve significantly after the implementation of the lockdown policy.

2.4.2 Effects of Lockdown on Air Quality Outcomes - Staggered DID Model

Since the lockdown policies have different timings across cities, this could introduce bias if there are unobserved factors affecting both the timing of the lockdown and air pollution levels. Therefore, I follow Sun & Abraham (2020) to construct the staggered DID model. I treat the lockdown timings as separate events. For each specific time, I calculate the dynamic treatment effect using the following regression equation:

$$Y_{it} = \sum_{g=1}^{e} \sum_{k \neq -1} \beta_{g,k} (1\{G_g = g\} * D_{it}^{k}) + X_{it} \times \alpha + \mu_i + \delta_t + \epsilon_{it} \qquad (2.6)$$

where g represents the event and k represents the relative week of the event. For example, -1 represents one week before the event, and 1 represents one week after the event. Only cities that have never experienced a lockdown are used as the control group. Finally, I obtain the weighted average of the coefficients β_k, where the weights are determined by the proportion of sample size for each group in period k to the total sample size across all groups in period k.

2.4.3 Effects of Lockdown Length on Air Quality Outcomes - Extended Equation

In addition to simply using the binary variables of lockdown and time, I also include the length of lockdown as an important explanatory variable. The equation takes the following form:

$$Y_{it} = f(Length_{it}) \times \beta + X_{it} \times \alpha + \mu_i + \delta_t + \epsilon_{it} \qquad (2.2)$$

$Length_{it}$ is a running variable that represents the number of days after the official lockdown date. To provide robust analysis, the function $f(Length_{it})$ take different functional forms to flexibly control for variations in air quality. They include (i) the linear model $(Length_{it})$, (ii) the linear model with the interaction term of the running variable and the treatment variable $(Length_{it} * Treat_{it})$, (iii) the quadratic model $\left(Length_{it}{}^2\right), (iv)$ the quadratic model with the interaction term of the running variable and the treatment variable $\left(Length_{it}{}^2 * Treat_{it}\right)$. β represent the effect of lockdown length on air quality.

2.4.4 Event-study Analysis

The implementation of lockdown measures may involve multiple factors, including the severity of the pandemic, government policies and decisions, public health awareness, and more.

While lock-downed cities may appear relatively random, encompassing large, medium, and small cities, it is indeed possible that the decision to implement lockdown measures could be correlated with the existing pollution levels in a city. For instance, areas with higher pollution levels, often associated with industrial development, may be more likely to implement lockdown measures. Because economically developed regions with higher population mobility might experience faster transmission of COVID-19, making it easier to justify and implement lockdown measures. To address this concern, a parallel test was conducted to examine whether there were significant differences in air quality between cities that implemented lockdown measures and those that did not prior to the implementation of the lockdown.

In addition, parallel tests can also help us to exclude several possible reasons that influence the validity of our study. For example, there may be already a declining trend in air pollutants. The first possible reason is that Chinese government implemented a lot of environmental regulations recently. The improvement in air quality may be driven by the set of environmental regulations. The second reason is that COVID-19 was outbreak during the Chinese spring festival. In this period, most of the industrial activities were suspended even though there isn't lockdown policy, thus the air quality will become better.

This parallel test aims to provide further evidence regarding the causal relationship between the lockdown measures and air quality by comparing the pre-lockdown air quality in cities that implemented the measures with cities that did not. If the trends in air quality before lockdown implementation are comparable and the air quality of the treatment group was improved more than that of the control group, then I can conclude our results in the baseline specifications are reliable. To test the reliability of the baseline model, I fit the following event study equation:

$$Y_{it} = \sum_{m=k, m\neq -1}^{M} Treat_{it,k} \times \beta^k + X_{it} \times \alpha + \mu_i + \delta_t + \epsilon_{it} \tag{2.3}$$

where $Treat_{it,k}$ is a set of dummy variables which equals 1 for treatment cities and 0 for control cities all the time. I put 7 days into one bin to avoid the trend test is not affected by the high volatility of the daily air pollution. The dummy for m = −1 is omitted in equation (2.3) so that the post-lockdown effects are relative to the period immediately before the launch of the policy. β^k measures the difference in air quality between cities in the treatment and control group in period k relative to the difference one week before the lockdown.

2.5 Results

2.5.1 Effects of Lockdown on Air Quality Outcomes – Baseline Model

I use equation (2.1) to explore the effects of lockdown on a set of air quality outcomes: AQI, $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, O_3. To eliminate the influence of heteroscedasticity, I take the logarithm for each variable in the robustness check part and examine the effect on each variable after taking the logarithm. The odd columns in Tables 5 and 6 represent the effect of lockdown on dependent variables while weather control variables such as precipitation, snow depth, temperature, temperature squared, are not included. The even columns represent the results when weather control variables are included. All the units of coefficients except AQI in Tables 9, 10 are $\mu g/m^3$.

The results are consistent with our expectations. No matter if I use original dependent variables or take logs of the dependent variables and add weather controls or not, the coefficients are negative and statistically significant except for the O_3. Column 1 in Table 5 shows that AQI reduced by 7.096 units in lockdown cities which is 7% of the mean AQI concentration compared to non-lockdown cities. The lower the value of AQI, the better the air quality. Therefore, it means the lockdown policy does improve air quality a lot. Lockdown policy is especially useful to reduce the concentration of PM_{10}. That is because PM_{10} emissions mainly come from pollution sources, such as chimneys and vehicles directly. Lockdown greatly reduces the pollution sources from industrial activities, the prohibition of gatherings, and unnecessary going out during the lockdown period. The concentration of O_3 increased after the lockdown policy but it is insignificant after I include weather control variables. All the coefficients are statistically significant, indicating the lockdown is a powerful measure to improve air quality.

Table 9. Effects of Lockdown on AQI, $PM_{2.5}$, and PM_{10}

	(1) AQI	(2) AQI	(3) $PM_{2.5}$	(4) $PM_{2.5}$	(5) PM_{10}	(6) PM_{10}
Lockdown	-7.096^{***}	-6.610^{***}	-2.800^{***}	-2.788^{***}	-13.285^{***}	-13.000^{***}
	(1.2848)	(1.3144)	(0.7630)	(0.7655)	(1.8126)	(1.8807)
Precipitation		-0.024^{***}		-0.009^{**}		-0.019^{***}
		(0.0043)		(0.0033)		(0.0041)
Snow depth		0.116^{***}		0.056^{*}		0.128^{***}
		(0.0283)		(0.0230)		(0.0315)
Temperature		-0.284^{*}		-0.646^{***}		-0.256
		(0.1439)		(0.1215)		(0.1652)
Temp2		0.016^{**}		0.005		0.012^{*}
		(0.0055)		(0.0046)		(0.0055)
Constant	65.117^{***}	61.893^{***}	38.875^{***}	44.291^{***}	67.356^{***}	64.439^{***}
	(0.0353)	(1.9777)	(0.0209)	(1.5676)	(0.0498)	(2.7741)
Observations	141662	141662	141662	141662	141655	141655

Notes: Robust standard errors in parenthesis are clustered at the city level. City and date fixed effects are included in the regression. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10. Effects of Lockdown on SO_2, NO_2, CO, and O_3

	(1) SO_2	(2) SO_2	(3) NO_2	(4) NO_2	(5) CO	(6) CO	(7) O_3	(8) O_3
Lockdown	-1.496^{***}	-1.009^{***}	-3.944^{***}	-3.968^{***}	-0.014	-0.010	4.395^{***}	1.455
	(0.2920)	(0.2834)	(0.4734)	(0.4766)	(0.0151)	(0.0153)	(0.9173)	(0.8817)
Precipitation		-0.002^{**}		-0.001		0.000^{**}		-0.024^{***}
		(0.0006)		(0.0009)		(0.0000)		(0.0028)
Snow depth		0.015^{**}		0.048^{***}		0.001^{*}		0.077^{***}
		(0.0053)		(0.0059)		(0.0003)		(0.0095)
Temperature		-0.325^{***}		-0.016		-0.009^{***}		1.392^{***}
		(0.0431)		(0.0361)		(0.0018)		(0.1037)
Temp2		0.013^{***}		0.001		0.000^{**}		0.066^{***}
		(0.0015)		(0.0013)		(0.0001)		(0.0038)
Constant	11.304^{***}	11.339^{***}	26.298^{***}	24.882^{***}	0.803^{***}	0.845^{***}	66.066^{***}	29.784^{***}
	(0.0080)	(0.4552)	(0.0130)	(0.5881)	(0.0004)	(0.0199)	(0.0252)	(1.4944)
N	141662	141662	141662	141662	141654	141654	141659	141659

Notes: Robust standard errors in parenthesis are clustered at the city level. City and date fixed effects are included in the regression. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.5.2 Effects of Lockdown on Air Quality Outcomes - Staggered DID Model

Tables 11 and 12 present the Staggered DID results for the analysis of air quality indicators, including AQI, PM2.5, PM10, SO2, NO2, CO, O3. These models aimed to assess the impact of a treatment variable on various pollutants while controlling for key environmental factors such as precipitation, snow depth, temperature, and its squared term. Across all models, the treatment variable consistently exhibited negative coefficients that were statistically significant. This suggests that the lockdown policy has led to adverse effects on air quality indicators which is good for air quality.

Furthermore, it is noteworthy to emphasize that the coefficients observed in the current analysis, while slightly smaller, broadly align with the results obtained from the Difference-in-Differences (DID) estimation. This consistency across methodologies indicates the robustness of our findings. Despite minor variations in the magnitude of coefficients, the overall directionality of the treatment effect remains consistent. This suggests that the observed impact of the treatment variable on air quality indicators is robust.

Table 11. Effects of Lockdown on AQI, $PM_{2.5}$, and PM_{10} - Staggered DID

	(1)	(2)	(3)
VARIABLES	aqi	pm	pm10
treat	-4.299***	-2.815***	-6.384***
	(0.343)	(0.343)	(0.343)
prec	-0.0404***	-0.00829*	-0.0329***
	(65.54)	(65.54)	(65.54)
snow	0.0953***	0.0601***	0.0342***
	(32.34)	(32.34)	(32.34)
temp	-1.076***	-0.826***	-1.156***
	(8.491)	(8.491)	(8.491)
temp2	-0.0851***	-0.0645***	-0.0813***
	(101.8)	(101.8)	(101.8)
Observations	19,764	19,764	19,764
R-squared	0.289	0.278	0.275
Ajusted R2	0.284	0.284	0.284

Note: sd in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12. Effects of Lockdown on SO_2, NO_2, CO, and O_3 - Staggered DID

	(1)	(2)	(3)	(4)
VARIABLES	so2	no2	co	o3
Treat	-1.070***	-5.671***	-0.0820***	7.069***
	(0.343)	(0.343)	(0.343)	(0.343)
Precipitation	-0.0165***	-0.00557***	0.000453***	-0.00652***
	(65.54)	(65.54)	(65.54)	(65.54)
Snow	0.0105***	0.0127***	0.000819***	0.0272***
	(32.34)	(32.34)	(32.34)	(32.34)
Temperature	-0.492***	-0.385***	-0.00940***	0.00704
	(8.491)	(8.491)	(8.491)	(8.491)
Temperature2	0.000246	-0.0144***	-0.000778***	0.0230***
	(101.8)	(101.8)	(101.8)	(101.8)
Observations	19,764	19,764	19,764	19,764
R-squared	0.182	0.285	0.286	0.229
Ajusted R2	0.284	0.284	0.284	0.284

Note: sd in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

2.5.3 Effects of Lockdown Length on Air Quality Outcomes

The pairwise correlation analysis revealed the relationship between lockdown length and air pollutant variables. As depicted in Table 13, lockdown length demonstrated a weak negative correlation with several air pollutants. Specifically, lockdown length exhibited negative correlations with the AQI (-0.17), $PM_{2.5}$ (-0.23), SO_2(-0.03) and CO (-0.18), although the correlations were generally modest. Conversely, Table 14 demonstrated the relationship between squared lockdown length and air pollutants, showing similar trends albeit with slightly different correlation coefficients. These findings suggest that longer lockdown durations may be associated with slightly lower levels of certain air pollutants, although the strength of these relationships is limited. Further investigation into the causal mechanisms underlying these associations is warranted

Table 13. Pairwise Correlation of Lockdown Length and Pollutant Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Length	1.00							
(2) AQI	-0.17	1.00						
(3) PM2.5	-0.23	0.90	1.00					
(4) PM10	-0.05	0.84	0.85	1.00				
(5) SO2	-0.03	0.29	0.25	0.32	1.00			
(6) NO2	0.32	0.43	0.41	0.48	0.38	1.00		
(7) CO	-0.18	0.51	0.60	0.50	0.34	0.37	1.00	
(8) O3	0.06	0.06	0.03	0.08	-0.01	-0.15	-0.19	1.00

Table 14. Pairwise Correlation of Squared Lockdown Length and Pollutant Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Length2	1.00							
(2) AQI	-0.13	1.00						
(3) PM2.5	-0.18	0.90	1.00					
(4) PM10	-0.01	0.84	0.85	1.00				
(5) SO2	-0.03	0.29	0.25	0.32	1.00			
(6) NO2	0.33	0.43	0.41	0.48	0.38	1.00		
(7) CO	-0.15	0.51	0.60	0.50	0.34	0.37	1.00	
(8) O3	0.08	0.06	0.03	0.08	-0.01	-0.15	-0.19	1.00

Additionally, I employ Equation (2.2) to study the causal relationship between lockdown duration and air pollutants under four different scenarios, analyzing data spanning from Dec 1st, 2019, to March 14th, 2020. The time period spans 50 days before and after the outbreak of COVID-19. The study investigates the impact of lockdown on air quality outcomes during the COVID-19 pandemic, incorporating the length of lockdown as a critical explanatory variable. The regression equation adopts a flexible approach, employing different functional forms of lockdown duration represented by a running variable post-official lockdown date. These functional forms include linear and quadratic models, and interaction terms with treatment variables, aiming to robustly control for variations in air quality.

Across the examined pollutants (AQI, PM2.5, PM10, SO2, NO2, CO, and O3), the findings highlight consistent trends. In both linear and quadratic models, an increase in lockdown duration is associated with a significant reduction in air pollutant concentrations, indicating an overall improvement in air quality. The analysis spans from Jan 1st, 2019, to Mar 14th, 2020.When I include the running variable, length of lockdown, in the interaction term, I find that the coefficients are negative and statistically significant. When the number of lock-downed days increases by one, the concentration of AQI decreases by 0.678, which is 0.472% of the standard deviation of AQI. I also find that the concentration of $\mathrm{PM}_{2.5}$ decreases by 0.604 $\mathrm{ug/m^3}$ per day under the lockdown policy, which is 0.277% of the standard deviation of $\mathrm{PM}_{2.5}$. The average concentration of $\mathrm{PM}_{2.5}$ is 49.14 $\mathrm{ug/m^3}$. The World Health Organization (WHO) has established $\mathrm{PM}_{2.5}$ guidelines recommending that the annual average concentration of $\mathrm{PM}_{2.5}$ should not exceed 10 $\mathrm{ug/m^3}$ and the 24-hour average concentration of $\mathrm{PM}_{2.5}$ should not exceed 25 $\mathrm{ug/m^3}$. This implies that, under the lockdown policies, it would take approximately 57 days to achieve the $\mathrm{PM}_{2.5}$ standard recommended by the WHO.

Moreover, the inclusion of interaction terms with treatment variables enhances the significance of this decline, emphasizing the effectiveness of prolonged lockdown measures in mitigating pollution levels. Each model accounts for various controls and fixed effects for cities and years to minimize potential confounding factors. The robustness of the analysis is further evidenced by the large sample size, with observations spanning 33,364 instances for each pollutant. These results provide valuable insights into the environmental consequences of

COVID-19 containment measures, informing policymakers and public health officials in designing effective strategies for managing air quality during global health crisis.

Table 15. COVID-19 Lockdowns and Air Pollution

VARIABLES	(1) AQI	(2) $PM_{2.5}$	(3) PM_{10}
Panel A: Linear model			
	-0.678***	-0.604***	-0.665***
	(0.036)	(0.029)	(0.044)
Panel B: Linear interaction model			
	-0.893***	-0.732***	-0.952***
	(0.058)	(0.047)	(0.065)
Panel C: Quadratic model			
	-0.009***	-0.010**	-0.007***
	(0.000)	(0.000)	(0.001)
Panel D: Quadratic interaction model			
	-0.0175***	-0.0145***	-0.0181***
	(0.000)	(0.000)	(0.001)
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	33364	33364	33364

Note: *** p<0.01, ** p<0.05, * p<0.1. Results of equation (2.2) under four different settings. Clustered errors in parentheses are robust to the city level. The running variable is number of days from the lockdown date. Model 1 uses running variable in linear form, Model 2 includes interaction of running variable and treatment variable, Model 3 includes quadratic term of running variable, Model 4 includes interactions of running variable with treatment variable. All regressions include city and year-fixed effects. Control variables are precipitation, temperature, squared temperature, and snow depth.

Table 16. COVID-19 Lockdowns and Air Pollution

VARIABLES	(1) SO_2	(2) NO_2	(3) CO	(4) O_3
Panel A: Linear model				
	-0.116***	-0.396***	-0.008***	0.318***
	(0.007)	(0.011)	(0.000)	(0.015)
Panel B: Linear interaction model				
	-0.0939***	-0.309***	-0.00649***	0.292***
	(0.014)	(0.015)	(0.001)	(0.021)
Panel C: Quadratic model				
	-0.00109***	-0.00146***	-0.000144***	0.00352***
	(0.000)	(0.000)	(0.000)	(0.000)
Panel D: Quadratic interaction model				
	-0.00186***	-0.00500***	-0.000126***	0.00534***
	(0.000)	(0.000)	(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	33364	33364	33364	33364

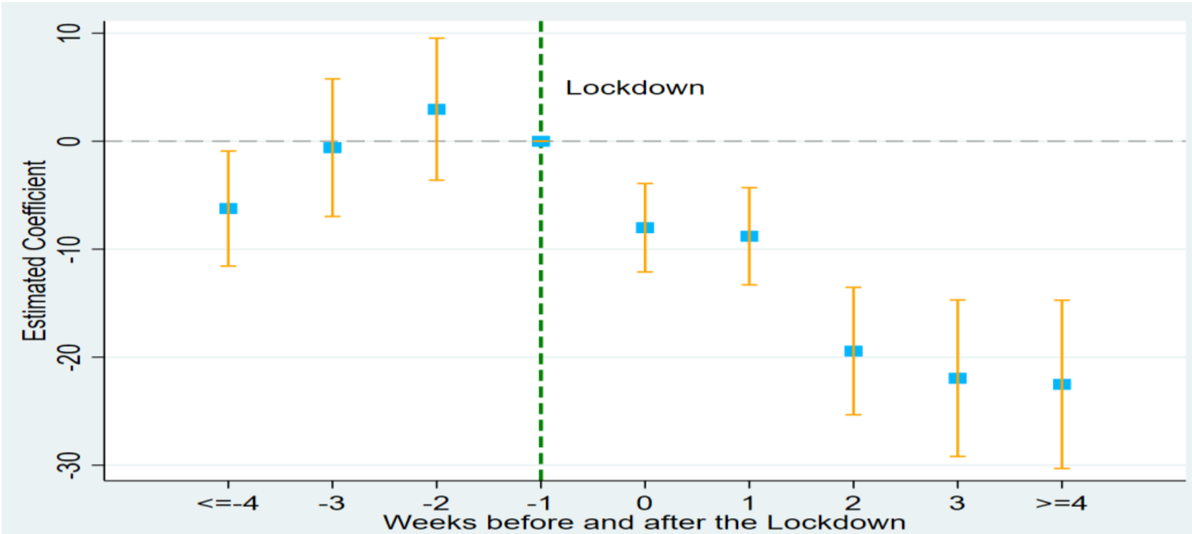
Note: *** p<0.01, ** p<0.05, * p<0.1. Results of equation (2.2) under four different settings. Clustered errors in parentheses are robust to the city level. The running variable is number of days from the lockdown date. Model 1 uses running variable in linear form, Model 2 includes interaction of running variable and treatment variable, Model 3 includes quadratic term of running variable, Model 4 includes interactions of running variable with treatment variable. Control variables are precipitation, temperature, squared temperature, and snow depth.

2.5.4 Event Study Analysis

Figure 2 illustrates the coefficients associated with $PM_{2.5}$ according to equation (2.3). The coefficient β^k quantifies the disparity in air quality between cities subjected to the lockdown measures and those without, during period k, relative to the difference observed one week prior to the lockdown. If k is less than 0, it represents the number of weeks before the implementation of the lockdown policy. If k is grea ter than 0, it represents the number of weeks during which the lockdown policy is being implemented. The analysis in Figure 2 spans from Jan 1st 2019, to Mar 14th 2020. This figure represents the differences between the treatment group and the control group before and during the implementation of the lockdown policy. It is evident that β^k approaches zero when K is smaller than -1, indicating that lock-downed and non-lockdown cities exhibited similar trends before the implementation of the lockdown policy. As K increases beyond 0, the coefficients become negative and larger in magnitude, aligning with our baseline findings. This suggests that the concentration of $PM_{2.5}$ in treatment group decrease after the implementation of lockdown policy compared to non-lockdown cities. Furthermore, the magnitude of the reduction increases over time, which aligns with the conclusions drawn in section 2.5.2.

I conduct a joint significance test to examine whether the coefficients before the lockdown are significantly different from zero. The null hypothesis is "$\beta^{-2} = \beta^{-3} = \beta^{-4} = 0$", and the resulting p-value is 0.1523 with an F-statistic of 1.77. Therefore, I do not have sufficient reason to reject the null hypothesis, indicating that there is no significant difference in air quality between the treatment group and the control group before the lockdown. In addition, I also conduct a joint significance test to examine whether the coefficients during the lockdown are significantly different from zero. The null hypothesis is "$\beta^{1} = \beta^{2} = \beta^{3} = \beta^{4} = 0$", and the resulting p-value is 0.0000 with an F-statistic of 10.95. Therefore, I have sufficient reason to reject the null hypothesis, indicating that there is significant difference in air quality between the treatment group and the control group during the lockdown. This indicates that before the implementation of the lockdown policy, the treatment group and the control group exhibit parallel trends. However, after the implementation of the lockdown policy, the treatment group shows a significant improvement in air quality compared to the control group, and the air quality continue to improve as the duration of the lockdown increased. Please refer to the appendix for additional results of the temporal analysis on other air pollutants.

Figure 11. Event Study Analysis of $PM_{2.5}$



2.5.5 Lockdown Lift Analysis

Starting from November 30, 2022, cities like Beijing, Guangzhou, and Shanghai announced significant relaxations of COVID-19 control measures to be implemented in December. The state media began extensively promoting the lower pathogenicity, lower severity, and lower mortality rates of the Omicron variant. The National Health Commission issued guidelines to strengthen vaccination efforts among the elderly. Sun Chunlan, known for her strong stance on zero-COVID policies, acknowledged the reduced virulence of the new variant, widespread vaccination, and accumulated medical experience, indicating that China's pandemic response was entering a "new phase with new tasks." This early signal marked the beginning of the relaxation of the zero-COVID policy.

The "optimized adjustment of control measures" included but was not limited to the following: Routine nucleic acid testing was no longer required for the general population, except for certain key personnel, with the recommendation that residents undergo testing only if necessary. Health codes became sufficient for accessing public transportation and most public places, eliminating the need for recent nucleic acid test records, except in enclosed entertainment venues like KTVs, internet cafes, and in places with vulnerable populations such as elderly care facilities and welfare homes. The registration requirement for the purchase of fever, cough, antiviral, and antibiotic medications was abolished. Mandatory nucleic acid testing upon arrival was canceled in some regions. By December 7, with the issuance of the "New Ten Measures," mainland China had effectively abandoned the "dynamic zero-COVID" policy, shifting towards coexistence with the virus.

Table 15, 16, and 17 present Difference-in-Differences analyses conducted over three different timeframes. Table 15 covers the period from January 1, 2022, to April 30, 2024. Table 16 focuses on one month before and after the cutoff date, December 7, 2022. Table 17 examines the week before and after the cutoff date.

From these tables, several key observations emerge: The first one is the consistent positive coefficients. Across all three tables, the coefficients for the impact of lifting lockdown measures on air quality indicators are predominantly positive and significant. This suggests that the relaxation of lockdown policies led to a deterioration in air quality.

The second one is that the coefficient magnitudes are different. The magnitude of these coefficients decreases as the timeframe extends. For instance, in the analysis around the week before and after the cutoff date (Table 17), the coefficients are notably large. The coefficient for PM10 is 53.43, with a corresponding mean value of 68.581. Similarly, the AQI coefficient is 39.54, against a mean of 57.579, and the PM2.5 coefficient is 23.84, with a mean of 33.235. These large coefficients indicate significant changes in air quality metrics immediately following the policy change.

The third one is that the impact diminishes over time. As the analysis timeframe extends, the coefficients shrink, indicating that the negative impact on air quality diminishes over time. For example, while the immediate post-lockdown period shows substantial increases in PM10, AQI, and PM2.5, the impact lessens in the longer-term analysis spanning over two years (Table 15). This trend suggests that the initial spike in pollution following the lifting of restrictions is a short-term effect, with air quality gradually stabilizing as time progresses.

Overall, the DID analyses across different timeframes reveal a clear pattern. The relaxation of lockdown measures leads to an immediate and significant rise in pollution levels, which gradually diminishes over time. This insight is crucial for understanding the environmental trade-offs of public health policies and for planning future interventions that can better balance public health, economic activity, and environmental sustainability.

Table 17. Long-term Air Quality Changes

VARIABLES	(1) AQI	(2) $PM_{2.5}$	(3) PM_{10}	(4) SO_2	(5) NO_2	(6) CO	(7) O_3
POST * TREAT	2.474***	1.323***	3.835***	0.102	0.311	0.00225	-1.258*
	(0.364)	(0.364)	(0.364)	(0.364)	(0.364)	(0.364)	(0.364)
Observations	284,859	284,352	284,099	284,571	284,544	284,471	284,676
R-squared	0.271	0.273	0.198	0.277	0.390	0.323	0.373
Ajusted R2	0.372	0.372	0.372	0.372	0.372	0.372	0.372

Note: Robust sd in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 18. Air Quallity Changes – 30 Days

VARIABLES	(1) AQI	(2) $PM_{2.5}$	(3) PM_{10}	(4) SO_2	(5) NO_2	(6) CO	(7) O_3
POST * TREAT	8.528***	4.353**	11.34***	1.000*	0.800	-0.0422**	5.058***
	(0.342)	(0.342)	(0.342)	(0.342)	(0.342)	(0.342)	(0.342)
Observations	19,961	19,931	19,946	19,941	19,946	19,947	19,947
R-squared	0.365	0.349	0.363	0.399	0.399	0.454	0.266
Ajusted R2	0.253	0.253	0.253	0.253	0.253	0.253	0.253

Note: Robust sd in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 19. Air Quallity Changes – 7 Days

VARIABLES	(1) AQI	(2) $PM_{2.5}$	(3) PM_{10}	(4) SO_2	(5) NO_2	(6) CO	(7) O_3
POST * TREAT	39.54***	23.84***	53.43***	1.661***	7.122***	0.0846***	8.259***
	(0.351)	(0.351)	(0.351)	(0.351)	(0.351)	(0.351)	(0.351)
Observations	4,392	4,387	4,389	4,387	4,389	4,388	4,388
R-squared	0.550	0.448	0.556	0.471	0.467	0.522	0.393
Ajusted R2	0.342	0.342	0.342	0.342	0.342	0.342	0.342

Note: Robust sd in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

2.5.6 Robustness Check

Tables 20 and 21 present the results of regression analyses examining the effect of lockdown length on various air quality indicators, including AQI (Air Quality Index), PM2.5, PM10, SO2, NO2, CO, and O3. It sapns from January 1 st 2019 to Mar 14th 2020. The analysis controls for factors such as precipitation, snowfall, temperature, and their quadratic terms, as well as city and date fixed effects. Upon incorporating the running variable, the length of lockdown, into the interaction term, I discovered that the coefficients exhibit a negative and statistically significant trend.

In Table 20, it is observed that longer lockdown durations are associated with decreases in AQI, PM2.5, and PM10 levels. This negative relationship is statistically significant, as indicated by the p-values. Specifically, with each additional day of lockdown, the concentration of AQI decreased by 0.239 units, accounting for approximately 0.472% of the standard deviation of AQI. Similarly, the concentration of PM2.5 exhibited a decline of 0.110 $\mathrm{ug/m^3}$ per day under lockdown measures, constituting around 0.277% of the standard deviation of PM2.5. It's noteworthy to mention that the annual average concentration of PM2.5 stood at 49.14 $\mathrm{ug/m^3}$. Against this backdrop, it becomes evident that the World Health Organization's (WHO) guidelines regarding PM2.5 concentrations are imperative. The WHO recommends an annual average PM2.5 concentration not exceeding 10 $\mathrm{ug/m^3}$, with a 24-hour average concentration limit of 25 $\mathrm{ug/m^3}$. Given the observed reductions in PM2.5 concentrations under lockdown policies, it would take approximately 220 days to meet the WHO's recommended standards for PM2.5 concentration levels.

Additionally, precipitation has a significant negative effect on AQI, PM2.5, and PM10, while snowfall is positively associated with these pollutants. Temperature shows a mixed effect, with the linear term negatively impacting AQI and PM2.5, and the quadratic term positively affecting them.

In Table 21, the analysis focuses on other pollutants such as SO2, NO2, CO, and O3. Similar to Table 12, the interaction term of lockdown length with treatment and post-lockdown periods shows negative coefficients for SO2 and NO2, indicating a reduction in these pollutants during longer lockdown periods. Precipitation has a significant negative effect on SO2 and O3 levels but not on NO2 and CO. Snowfall is positively associated with SO2 and NO2 but not significantly with CO and O3. Temperature and its quadratic term show mixed effects across different pollutants. Overall, these findings suggest that longer lockdown durations are generally associated with improvements in air quality, as indicated by reductions in various pollutants. However, the effects of weather factors such as precipitation, snowfall, and temperature are nuanced and vary across different pollutants.

Table 20. Effects of Lockdown Length on AQI, PM2.5 and PM10

	(1)	(2)	(3)
VARIABLES	AQI	$PM_{2.5}$	PM_{10}
Length*Treat*Post	-0.239***	-0.110***	-0.431***
	(0.043)	(0.023)	(0.072)
Precipitation	-0.0242***	-0.00871***	-0.0192***
	(0.004)	(0.003)	(0.004)
Snow	0.117***	0.0570**	0.130***
	(0.028)	(0.023)	(0.031)
Temp	-0.285**	-0.646***	-0.258
	(0.144)	(0.121)	(0.165)
$Temp^2$	0.0162***	0.00467	0.0116**
	(0.017)	(0.005)	(0.006)
Observations	141,662	141,662	141,655
R-squared	0.452	0.459	0.405
Adjusted R2	0.449	0.456	0.402

Notes: Robust standard errors in parenthesis are clustered at the city level. City and date fixed effects are included in the regression. *** p<0.01, ** p<0.05, * p<0.1

Table 21. Effects of Lockdown Length on SO2, NO2, CO and O3

VARIABLES	(1) SO_2	(2) NO_2	(3) CO	(4) O_3
Length*Treat*Post	-0.0270***	-0.0981***	-0.000141	-0.0489*
	(0.008)	(0.013)	(0.000)	(0.028)
Precipitation	-0.00153***	-0.00106	0.000145***	-0.0235***
	(0.001)	(0.001)	(0.000)	(0.003)
Snow	0.0148***	0.0486***	0.000699**	0.0777***
	(0.005)	(0.006)	(0.000)	(0.009)
Temp	-0.325***	-0.0166	-0.00908***	1.392***
	(0.043)	(0.036)	(0.002)	(0.104)
$Temp^2$	0.0134***	0.000879	0.000155***	0.0663***
	(0.001)	(0.001)	(0.000)	(0.00)
Observations	141,662	141,662	141,654	141,659
R-squared	0.516	0.659	0.521	0.519
Adjusted R2	0.513	0.657	0.519	0.516

Notes: Robust standard errors in parenthesis are clustered at the city level. City and date fixed effects are included in the regression. *** p<0.01, ** p<0.05, * p<0.1.

2.6 Conclusion

In this study, I estimate the impact of the lockdown on various air pollutants including AQI, $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3. After accounting for weather controls, I find that in the treatment cities, both AQI and $PM_{2.5}$ show significant improvements, with a reduction of 6.610 and 2.788 ug/m^3 respectively, compared to the control cities.

Additionally, I observe a daily decrease of 0.239 in AQI, which corresponds to a reduction of 0.472% of the standard deviation of AQI. Similarly, the concentration of $PM_{2.5}$ has shown a daily decrease of 0.110 ug/m^3 under the lockdown policy, accounting for 0.277% of the standard deviation of $PM_{2.5}$ from the implementation of the lockdown policy until March 14th, 2020.

After lifting the Lockdown policy, the analysis spans from 7 days before and after the cutoff date indicates that the AQI coefficient is 39.54, against a mean of 57.579, and the PM2.5 coefficient is 23.84, with a mean of 33.235. It means that the relaxation of lockdown measures leads to an immediate and significant rise in pollution levels. But when I do the analysis over longer periods, the coefficients decreases representing the effects gradually diminishes over time.

To ensure the robustness of the results and rule out the possibility of systematic differences between the treatment and control groups, I conduct an event study analysis. The findings indicate that the two groups exhibit a parallel trend before the implementation of the lockdown, lending further support to the validity of the results. Moreover, the air quality in the lockdown cities demonstrates significant improvements compared to the non-locked-downed cities.

Chapter 3 Carbon Emissions Trading System, Air Quality and Mental Health - Evidence from China

3.1 Introduction

China has established a Carbon Emission Trading System (ETS) as part of its efforts to mitigate climate change and reduce greenhouse gas emissions. Understanding the impact of ETS on air quality and mental health is of great importance. It can inform us of the benefits of ETS in China and provide policy implications to reduce air pollution and improve social welfare. Air pollution is a serious and urgent problem in China. Air quality imposes negative effect on heart disease, cardiovascular disease, lung disease, and infant mortality. Apart from physical health, it also has effects on socio-economic outcomes, like productivity, cognitive performance, etc. This paper presents new evidence on the impact of air quality on mental health in the natural experiment of ETS in China.

Some literature studies the effect of ETS on air pollution and the relationship between air quality and mental health. For example, Yan et al. (2020) employ DID method and mediating effect model to assess the impact of ETS pilot on air pollution. Zhang et al. (2017) use OLS model to test the impact of air quality on people's happiness and subjective well-being from 2012 to 2014. Chen et al. (2018) presents an IV method -instrumented by thermal inversions- to study the impact of air quality on people's mental health in a short time frame.

The purpose of this paper is to explore the impact of the ETS on air quality and mental health. It is expected that the implementation of ETS can improve air pollution by facilitating the efficient trading of emissions. Implementing a GHG ETS not only curbs CO_2 emissions but also leads to a reduction in air pollution by incentivizing industries to adopt cleaner technologies and improve energy efficiency. This dual benefit promotes public health, environmental sustainability, and economic growth simultaneously. The objective is to investigate whether ETS has indeed achieved this outcome. Furthermore, if ETS has indeed improved air quality, the study aims to examine whether it has indirectly contributed to the improvement of people's mental well-being. The implementation of ETS may affect mental health from several channels: air quality, economy and employment. Good air quality will improve people's mental health. However, the impact of ETS on economy and unemployment is not clear enough. The existing studies find that ETS have mild negative effect on economy, but also depends on the pillars of the local economy. It also finds that ETS increased unemployment in electricity, coal and construction industry. But from long-term, it has positive effect on employment.

This paper makes several key contributions. First, to the best of my knowledge, it is the first study to explore the benefits of Carbon ETS for mental health. Previous research has primarily focused on the impact of ETS on air quality (Yan et al. 2020), industrial output (Huang et al. 2021), economy (Wang et al. 2015), green total factor productivity (Hou et al. 2019), technological innovation, and other related areas. Thus, this paper provides a novel perspective for assessing the cost-effectiveness of ETS policies. Second, while previous studies mainly examined the SO_2 ETS policy implemented in China in 2007, this paper specifically investigates the carbon emission trading system. By focusing on carbon emissions, it expands the understanding of the effects of ETS on environmental and health outcomes. Third, in exploring the impact of ETS on mental health, this paper considers heterogeneity, such as differences between urban and rural areas, educational attainment, health status, age, and other factors. This consideration allows for a more comprehensive analysis of how ETS may influence mental well-being across various contexts. Overall, these contributions shed new light on the potential benefits of ETS, particularly in terms of mental health outcomes, and provide valuable insights for policymakers and researchers interested in evaluating the effectiveness of ETS policies.

In this study, I utilize the DID method to estimate the effects of the ETS on air quality and mental health. Mental health is indicated by CESD20 which is a scale used to assess levels of psychological distress, consisting of 20 items designed to measure indicators of depression, anxiety, and stress. I obtained the date from three sources. The air quality data comes from National Environmental Monitoring Center, the mental health and socio-economic controls are from Chinese Family Panel Studies (CFPS), the weather data is from the China Meteorological Data Service Center (CMDC). The results reveal a significant improvement in air quality following the implementation of ETS, as indicated by a decrease in AQI by 10.98 units, $\mathrm{PM}_{2.5}$ by 7.92 $\mathrm{ug/m^3}$, and PM_{10} by 13.23 $\mathrm{ug/m^3}$. Furthermore, the analysis shows that the CESD20 score of individuals in Fujian Province decreased 3.7% after the pilot of ETS, indicating a positive impact on mental well-being.

The subsequent sections of this paper are structured as follows. The section 3.2 below presents some background information of ETS in China. Section 3.3 offers an extensive literature review on the subject matter, providing an overview of the existing research. In Section 3.4, I present the data utilized in this study along with their sources. Section 3.5 outlines the empirical model employed to analyze the data. The findings of our analysis are presented in Section 3.6. The paper concludes in section 3.7.

3.2 Background

According to "Our World in Data" at the University of Oxford, China emitted 10.67 billion tons of carbon dioxide in 2020, ranking first in the world. India and the United States also emitted a large amount of CO_2 in 2020. The emission of CO_2 in China increased rapidly since

2000. Carbon dioxide is an important driver of the greenhouse effect and climate change. At the same time, the release of CO is accompanied by the combustion of fossil fuels and energy and releases a large amount of other harmful gases, such as SO_2, NO_2, CO, etc., which seriously threaten people's physical and mental health.

In 2011, in accordance with the requirements of the "Twelfth Five-Year Plan" on "gradually establishing a carbon emissions trading market", China launched carbon emissions trading pilots in seven provinces and cities including Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen to reduce carbon dioxide emissions and improve air quality. In 2013, seven local pilot carbon markets began to be traded online one after another, effectively promoting the emission reduction of greenhouse gases by enterprises in the pilot provinces and cities. In December 2016, Fujian Province launched the carbon trading market, as the eighth domestic carbon trading pilot province. In July 2021, the high-profile national carbon market officially began to be traded online. Table 22 shows the specific time and price of the ETS market in China. I aim to explore the impact of ETS on air quality, furthermore, adult mental health.

Table 22. The Basic Situation and Features of Seven Pilots

Region	Emissions covered	Launch time	Enterprise selected	Industry involved	Trading platform	First price of carbon
Shenzhen	40%	6/18/2013	635	Electricity and other 26 carbon emissions industries	Shenzhen Climate Exchange	28 Yuan/ton ($4.57)
Guangdong	58%	9/11/2013	830	Iron and steel, cement, power and petrochemical industries	China Emissions Exchange	61 Yuan/ton ($9.95)
Shanghai	57%	11/26/2013	191	Iron and steel, Chemical industry, Petroleum chemistry Electric power, Building including hotel, shopping Aviation, Ports, Airport, etc.	Shanghai Environment and Energy Exchange	First transaction prices were 27 Yuan/ton ($4.40), 26 Yuan/ton ($4.24), 25 Yuan/ton ($4.08)
Beijing	40%	11/28/2013	490	Heat supply power, thermal power supply and other industries in the ‘direct’ field; manufacturing industry and large public buildings.	China Beijing Environment Exchange	50 Yuan/ton ($8.15)
Tianjin	50-60%	12/27/2013	114	Iron and steel, chemicals, electricity and heat, petrochemical, oil and gas in the ‘indirect’ areas	Tianjin Climate Exchange	28 Yuan/ton ($4.57)
Hubei	33%	4/2/2014	153	Electricity. Steel, cement, chemicals and other 12 industries	China Hubei Emission Exchange	20 Yuan/ton ($3.26)
Chongqing	39.5%	6/19/2014	254	The industrial enterprises over 20,000t of carbon dioxide emissions	Chongqing Carbon Emissions Trading Center	30-30.15 Yuan/ton ($4.89-5.13)

3.3 Literature Review

Most of the literature employ CGE model to simulate the air quality and health co-benefits of ETS in China. Cao et al. (2021) employs CMAA model to test the environmental and health effects of ETS in Hubei province. The simulation shows the ETS improved air quality in large parts of Hubei but the concentration of $PM_{2.5}$ increased in some major cities resulting in negative impacts on human health locally. Chang et al. (2020) find the ETS bring reduction of $PM_{2.5}$ concentration from 3% to 12% and the net health benefit would be around US$100 using the Regional Emissions Air Quality Climate Health Model. Some literature uses empirical methods to study the effects. Weng et al. (2022) employs a two-way fixed-effect model to estimate the causal relationship between daily carbon trading volumes and air pollution from 2015 to 2020. Results show that a one percent increase in daily carbon trading volumes leads to a reduction of 0.23% in $PM_{2.5}$ and 0.26% in PM_{10}. Yan et al. (2020) employ DID method and mediating effect model to assess the impact of ETS pilot on air pollution. Huang et al. (2021) integrates the propensity score matching method and multi-period DID method to examine the impacts of ETS on industrial output and pollution emissions. They find that the implementation of the ETS was conducive to increasing industrial output and reducing emissions.

Previous studies evaluated the impacts of ETS from different perspectives, such as impacts on Green Productivity Performance (Yang et al. 2021), economy (Marin et al. 2018), technologies (Mo et al. 2016; Bel and Joseph, 2018) and physical health(Chang, Shiyan, et al 2020.; Farrell et al. 2004). There are several papers examining the causal effect of air pollution on mental health. Zhang et al. (2017) employ fixed effects OLS model to estimate the effect of air pollution on hedonic happiness and the rate of depressive symptoms. Chen et al. (2018)

presents an IV method - instrumented by thermal inversions - to study the short run impact of air quality on people's mental health. Ferreira et al. (2013) analyze the relationship between air quality and subjective well-being in Europe using fixed effects OLS model. All these papers find negative impacts of air pollutants on mental health. Although some papers study the impact of air quality on mental health and the impact of ETS on many aspects, there is no paper that explores the direct effect of ETS on mental health. Mental health has become an increasingly serious problem in modern society. It is of great significance to study the impact of carbon emission market policies on mental health, which can better evaluate the benefits of the carbon emission market and health expenditures.

3.4 Empirical Strategy

3.4.1 The Effects of ETS Pilot Scheme on Air Quality

I use the DID method to test the impact of ETS on air quality and the equation takes the following from:

$$P_{ct} = \alpha_0 + \alpha_1 Post_t * Treat_c + \alpha_2 X_{ct} + \alpha_3 W_{ct} + \mu_m + \mu_y + \gamma_c + \varepsilon_{ct} \tag{3.1}$$

where the subscript c accounts for county and t accounts for daily time variable. P_{ct} is the air quality index for county c at time t. $Post_t$ is a dummy variable indicating whether it is before or after the pilot of emission trading system in county c and time t. If it is after the implementation time, then it equals 1, otherwise, it equals 0. $Treat_c$ is also a dummy variable representing whether county c is a pilot county or not. There are eight provinces and cities that piloted the ETS from 2013 and Fujian implemented ETS in 2016. Because the air quality data before 2013 is not available in most provinces, I use Fujian Province as the treatment group and provinces that never implemented the ETS as the control group. If it is Fujian province, then $Treat_c$ equals to 1. If the province or cities didn't implement the ETS in 2013 and 2016, $Treat_c$

equals to 0. X_{ct} is a set of socio-economic control variables, like population size, GDP, etc. W_{ct} is a set of weather control variables, like temperature, precipitation, and snow depth. I also control for year-month fixed effect to exclude the interference of seasonality. County fixed effects are also included in the model to exclude the influence of time-invariant variables.

3.4.2 The Effects of ETS Pilot Scheme on Mental Health

There is a high possibility that the ETS pilot will also increase people's happiness and reduce the rate of depressive symptoms. I use the DID model to evaluate the effect of ETS on mental health and the DID model is constructed as follows:

$$MH_{imy} = \alpha_0 + \alpha_1 Post_{my} * Treat_i + \alpha_2 X_{imy} + \alpha_3 W_{cmy} + \mu_m + \mu_y + \gamma_c + \varepsilon_{icmy} \qquad (3.2)$$

Where the subscript i accounts for the individual i, c accounts for the county and m accounts for the monthly time variable in year y. For example, MH_{icmy} is the mental health index for individual i, in county c, and at month m in year y. $Post_{my}$ is a dummy variable indicating whether it is after or before the pilot of emission trading system in county c. If it is after the implementation time, then it equals 1, otherwise, it equals 0. Treat_i is also a dummy variable representing whether county c is a pilot city or not. If the interviewees live in Fujian provinces, then Treat_c equals 1, otherwise it equals 0. X_{it} is a set of socio-economic control variables, like age, the square of age, educational outcomes, marital status, income, etc. W_{ct} is a set of weather control variables, like temperature, precipitation, and snow depth. I also control for year-month fixed effect and county fixed effects to exclude the interference of seasonality and time-invariant variables.

3.4.3 Event Study Analysis

The assumption of the DID model is that the treatment group and the control group have a parallel trend before the policy implementation. If there are significant differences between the two groups before the policy implementation, even if I observe significant differences in outcomes between the groups after the policy, I cannot attribute those differences solely to the policy. Therefore, it is important to test whether there are significant differences in air quality and mental health between the control group and the treatment group before the policy implementation. The event study analysis takes the following model:

$$Y_{it} = \sum_{m=k,m\neq -1}^{M} Treat_{it,k} \times \beta^k + X_{it} \times \alpha + \mu_i + \delta_t + \epsilon_{it} \tag{3.3}$$

Where Y_{it} is the outcome variable, the mental health score for individual i at time t. $Treat_{it,k}$ is a set of dummy variables which equals 1 for treatment cities and 0 for control cities all the time. I put one month into one bin to avoid that the trend test is not affected by the high volatility of the daily air pollution and mental health. The dummy for $m = -1$ is omitted in equation (3.3) so that the post-ETS effects are relative to the period immediately before the launch of the policy. β^kmeasures the difference in air quality or mental health between cities or individuals in the treatment group and otherwise in period k relative to the difference one week before the ETS policy. When k is less than -1, β^k should be 0, indicating no significant difference between the control and the treatment group. When k is greater than 0, the coefficient should be negative, indicating an improvement in air quality and mental health in the control group after the policy implementation.

3.5 Data

3.5.1 Air Quality

Data on air quality, such as AQI, $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO are obtained from the China National Environmental Monitoring Center (CNEMC), which is affiliated to the Ministry of Environmental Protection of China. The CNEMC publishes hourly Air Quality Index and specific air pollutants including $PM_{2.5}$, PM_{10}, O_3, SO_2, NO_2 and CO for around 1400 monitoring stations from January 2013. But most of the cities pilot carbon-emission trading system in 2013 except Fujian province. So, when I study the impact of carbon emission trading system, I used Fujian province which implemented carbon emission trading system in 2016 as the treatment group and other province which didn't implement carbon emission trading system in 2013 and 2016 as control group. I explore the effect of ETS on air quality from Jan. 1st, 2015, to Dec. 31st, 2017. I use the monitoring station information to convert the data at the monitoring station level to the city level, and then match the air quality data with the CFPS data by city and time.

3.5.2 Mental Health and Socio-economic Controls

I obtain mental health and socio-economic controls from Chinese Family Panel Studies (CFPS). CFPS is implemented every two years by the China Social Science Survey Center (ISSS) of Peking University since 2010. The current survey results include 2010, 2012, 2014, 2016, 2018, and 2020. The CFPS sample covers 25 provinces, cities or autonomous regions, the target sample size is 16,000 households, and the survey objects include all family members in the sample households. The CFPS survey includes four primary types of questionnaires, namely the community questionnaire, family questionnaire, adult questionnaire, and children's questionnaire. I mainly use the adult questionnaire among them. The questions I use include: "How often have you felt depressed or depressed in the last month"; "How often you feel nervous in the last month"; "How often you feel restless and have trouble staying calm in the last month"; "How often you feel hopeless for the future in the last month"; "How often you have difficulty doing anything in the last month"; "How often you think life is meaningless in the last month". The responses include five categories, namely never, sometime, half of the time, often, almost every day. This survey also includes age, sex, highest education, and income. I include them as control variables. It also has county ID, interview year and month so that I can match the mental health data with air quality and weather control variables.

3.5.3 Weather Controls

I obtain the weather data from the China Meteorological Data Service Center (CMDC), which is affiliated to the National Meteorological Information Center of China. The CMDC records daily maximum, minimum, and average temperatures, precipitation, relative humidity, wind speed, snow depth and sunshine duration for 820 weather stations in China. I use average temperature, aggregate precipitation, and snow depth for the month prior to the interview.

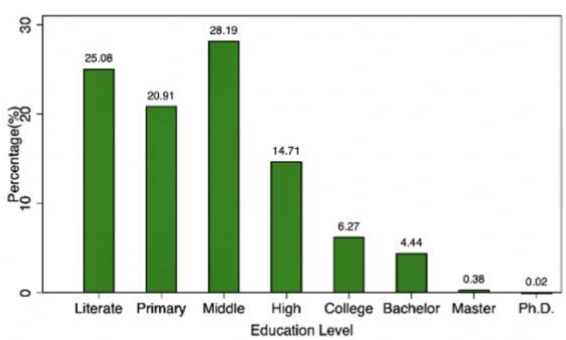
3.5.4 Summary Statistics

Table 23 provides a summary of the descriptive statistics for AQI, $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3. The unit of measurement for these variables is micrograms per cubic meter ($\mu g/m^3$), except for AQI. The results show that in the treatment group (Fujian province), all air quality indicators exhibited a decrease after the implementation of the ETS. In the control groups, the air quality indicators also decreased, but to a lesser extent compared to the treatment group. In Figure 12, 13, and 14, I present the education level, marital status, and health status of the individuals participating in the mental health survey. It is observed that most participants had not received higher education, were married, and reported being in relatively good health.

Table 23. Summary Statistics for Air Quality-Related Indicators

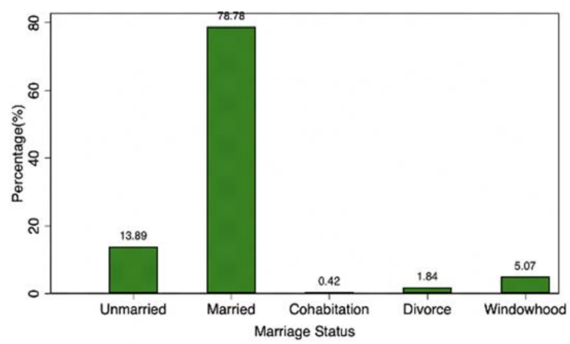
	Fujian				Controls			
	Before ETS		After ETS		Before ETS		After ETS	
	N	mean	N	mean	N	mean	N	mean
AQI	5135	58.86	2448	52.14	841303	79.78	418632	75.52
$PM_{2.5}$	5116	33.31	2442	30.07	832495	51.1	416884	46.42
PM_{10}	4805	64.3	2312	57.51	780735	92.53	395015	86.06
SO_2	5128	21.19	2439	11.25	837902	29.31	417471	21.72
NO_2	5124	24.53	2437	21.64	837167	26.67	417381	26.38
CO	5122	0.92	2436	0.64	833892	1.07	417077	0.980
O_3	5114	89.92	2436	67.02	836387	73.49	417771	82.57
CESD20	780	33.05	416	30.5	52422	32.5	25866	32.9

Figure 12. Percentage of Education Level



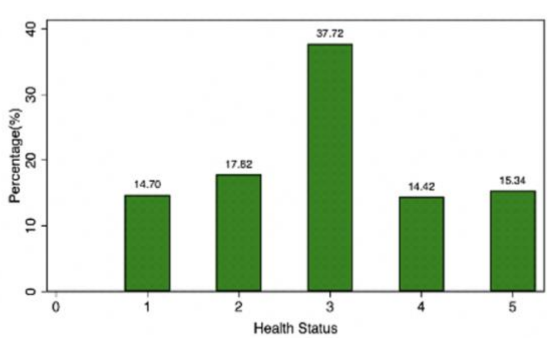
Notes: Literate/semi-literate: 1; Primary: 2; Middle: 3; High: 4; College: 5; Bachelor: 6; Master: 7; Ph.D.: 8

Figure 13. Percentage of Marriage Status



Notes: Unmarried: 1; Married: 2; Cohabitation: 3; Divorce: 4; Widowhood: 5

Figure 14. Percentage of Health Status



Notes: 1: Pretty healthy; 2: Very healthy; 3: Relative healthy; 4: Weak; 5: Unhealthy

3.6 Results

3.6.1 The Impacts of ETS on Air Quality

China piloted ETS in seven cities in 2013 and piloted ETS in Fujian province in 2016. The first analysis I did was to restrict my analysis to Fujian province and other provinces except for the seven provinces that implemented ETS in 2013. I used Fujian Province as the Treatment group and other provinces except for the seven provinces that implemented ETS in 2013 as the control group. In Table 24, columns (1), (2) and (3) show the regression results for $\mathrm{AQI}, \mathrm{PM}_{2.5}$ and PM_{10}. The coefficients of ETS on $\mathrm{AQI}, \mathrm{PM}_{2.5}$ and PM_{10} are negative and statistically significant. After the implementation of ETS, the AQI decreased 10.98, $\mathrm{PM}_{2.5}$ decreased by 7.92 $\mathrm{ug/m^3}$ and PM_{10} decreased by 13.23 $\mathrm{ug/m^3}$ which corresponds 18.7%, 23.8% and 20.6% of the mean value. It means that the ETS significantly improved air quality. And the coefficients of Time on $\mathrm{AQI}, \mathrm{PM}_{2.5}$ and PM_{10} are all positive and statistically significant. That means the air quality tends to deteriorate.

Table 24. The Impacts of ETS on AQI, $PM_{2.5}$, and PM_{10} – Fujian Province(Treatment Group)

	(1)	(2)	(3)
	AQI	$\mathrm{PM}_{2.5}$	PM_{10}
ETS*Post	-10.98***	-7.92***	-13.23***
	(1.37)	(1.13)	(2.27)
Province F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
N	1267,518	1267,518	1267,518
R^2	0.1122	0.1314	0.0711
Adj. R^2	0.1122	0.1314	0.0711

Notes: This analysis spans from 2013 to 2018. Standard errors are clustered by province and in parentheses. Statistical significance: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

By expanding the analysis to include all provinces that have implemented emission trading system (ETS) policies as the treatment group and those that have never implemented ETS policies as the control group, I have further broadened the scope of our analysis. This extended analysis involves more treatment provinces, potentially providing us with a more comprehensive understanding and deeper insights into the impact of ETS on air quality. The results from Table 25 indicate that the implementation of ETS policies has led to significant negative impacts on the AQI, PM2.5, and PM10 which is good for air quality. The higher the AQI, PM2.5 and PM10, the worse the air quality. Specifically, following the implementation of ETS policies, AQI decreased by 11.26, PM2.5 decreased by 8.032 ug/m^3, and PM10 decreased by 15.01 ug/m^3. This further underscores the positive role of emission trading systems in improving air quality.

Table 25. The Impact of ETS on AQI, $PM_{2.5}$, and PM_{10} – All 7 Provinces(Treatment Group)

	(1)	(2)	(3)
	AQI	$PM_{2.5}$	PM_{10}
ETS*Post	-11.26***	-8.032***	-15.01***
	(2.36)	(1.63)	(2.78)
Province F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
N	1312,526	1312,526	1312,526
R^2	0.1122	0.1314	0.0711
Adj. R^2	0.1122	0.1314	0.0711

Notes: This analysis spans from 2010 to 2018. Standard errors are clustered by province and in parentheses. Statistical significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Compared to solely using Fujian province as the treatment group, the effect of ETS becomes even more pronounced when adding these seven provinces as the experimental group, indicating a stronger improvement in air quality. This could likely be attributed to the fact that cities like Beijing, Shanghai, and Shenzhen, serving as representatives of economically developed regions in China, possess higher levels of industrialization and population density. Given their heightened economic activities and population density, the issue of air quality in these regions may be more acute, thus rendering the impact of ETS more significant. The distinctive economic and demographic structures of these areas may result in higher levels of pollution emissions, making ETS policies particularly crucial for enhancing air quality in these regions.

3.6.2 The Impact of ETS on Depression

I conduct the analysis from 2015 to 2020. Column (1) represents the results for CESD20 and column (2) represents results for the log of CESD20 scores. From Table 26, we can see that the CESD20 score for people in Fujian Province decreased 1.1115 which is 3.7% of the mean value after the pilot of ETS and the coefficient is statistically significant. We can also see that there is a trend that the CESD20 score increases. From the fourth row, we can see that people are more likely to get depressed as they get old. Compared with female, male has lower CESD20 score which means male are less likely to get depressed. In addition, there is a strong relationship between health status and CESD20 score. The coefficients on health status become larger when people get less healthy, and the coefficients are always statistically significant. That means, the healthier people are, the less likely they are to be depressed. Conversely, the less healthy they are, the more likely people are to be depressed. I also find that education can help reduce depression. The higher education people receive, the lower the CESD20 score they report. Marriage status also has significant effects on people's happiness. The coefficients of marriage and widowed on CESD20 are statistically significant while divorce and cohabitation are not. That means marriage can help reduce depression while widow will make people depressed.

In addition to examining the impact of ETS on depression in the general public, I also conducted separate analyses to investigate the effects of ETS on individuals with moderate depression and severe depression. The CESD questionnaire consists of a total of 20 questions, with a maximum score of 3 for each question. Therefore, the total score ranges from 0 to 60.

Scores below 15 indicate no depression, scores between 15 and 20 indicate mild depression, scores between 20 and 25 indicate moderate depression, and scores above 25 indicate severe depression.

Table 26. The Impacts of ETS on Mental Health

	CESD20	log (CESD20)
ETS * Post	-1.1115***	-0.0335***
	(8.7870)	(8.7621)
Treat	-0.5847*	-0.0197**
	(-2.6628)	(-2.9681)
Post	0.6237***	0.0206***
	(4.3195)	(4.5486)
Age	0.1166***	0.0032***
	(4.2321)	(3.9395)
Age*Age	-0.0017***	-0.0000***
	(-5.4622)	(-5.4845)
Male	-0.9311***	-0.0287***
	(-11.1273)	(-11.4950)
Very Healthy	1.1109***	0.0380***
	(5.9900)	(6.4561)
Relative Healthy	2.9688***	0.0953***
	(15.3650)	(16.4042)
Weak	4.7363***	0.1496***
	(22.4593)	(22.4405)
Unhealthy	9.5468***	0.2786***
	(34.1741)	(34.1511)
Primary	-0.8752***	-0.0250**
	(-3.9000)	(-3.6161)
Middle	-1.5421***	-0.0443***
	(-4.4716)	(-4.1898)
High	-1.8533***	-0.0529***
	(-5.2497)	(-5.0047)
College	-2.1476***	-0.0612***
	(-5.6725)	(-5.2568)
Bachelor	-2.4614***	-0.0696***
	(-5.0472)	(-4.7544)
Master	-2.7167***	-0.0754***
	(-4.4237)	(-3.7953)
Ph.D.	-2.7615	-0.0724
	(-1.3536)	(-1.0996)
Marriage	-0.9098***	-0.0251***
	(-4.4652)	(-4.2552)
Cohabitation	-0.1000	0.0024
	(-0.1502)	(0.1195)
Divorce	-0.2811	-0.0101
	(-1.4929)	(-1.7287)
Widowed	1.5828**	0.0460***
	(3.6035)	(3.7899)
N	34404	34404
R^2	0.1503	0.1461
Adj. R^2	0.1495	0.1453

Notes: t statistics in parentheses. The standard errors are clustered at province level. Statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

From Table 27, we can observe that after the implementation of ETS, there was a decrease in CESD scores for individuals with moderate depression and severe depression. This suggests that the implementation of ETS improved the mental health of individuals with moderate and serious depression. The improvement in mental health is larger for people with moderate depression compared with people with serious mental health problems. From Table 27, we can see that the CESD20 score for moderate depressed people decreased 0.93 after the pilot of ETS and the coefficient is statistically significant.

Table 27. The Impact of ETS on Moderate and Severe Depressed People

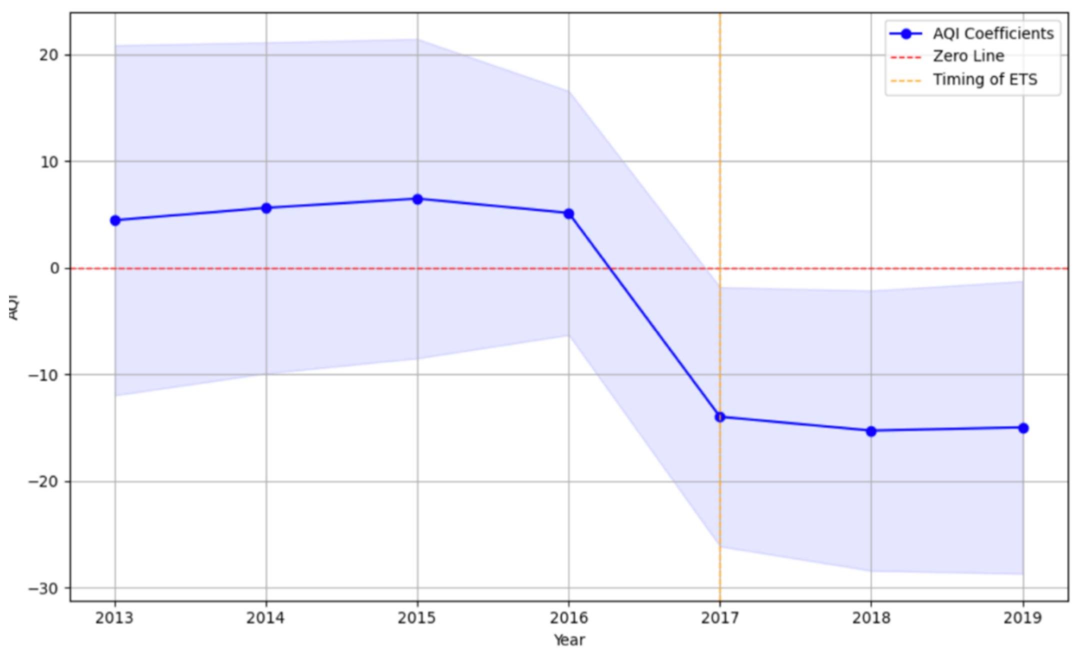
	Moderate Depression		Severe Depression	
	CESD20	log (CESD20)	CESD20	log (CESD20)
ETS * Post	-0.93^{*}	-0.063^{*}	-0.62^{*}	0.056^{*}
	(0.82)	(0.058)	(0.47)	(0.05)
Age	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes
Health	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered in province level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.6.3 Event Study Analysis

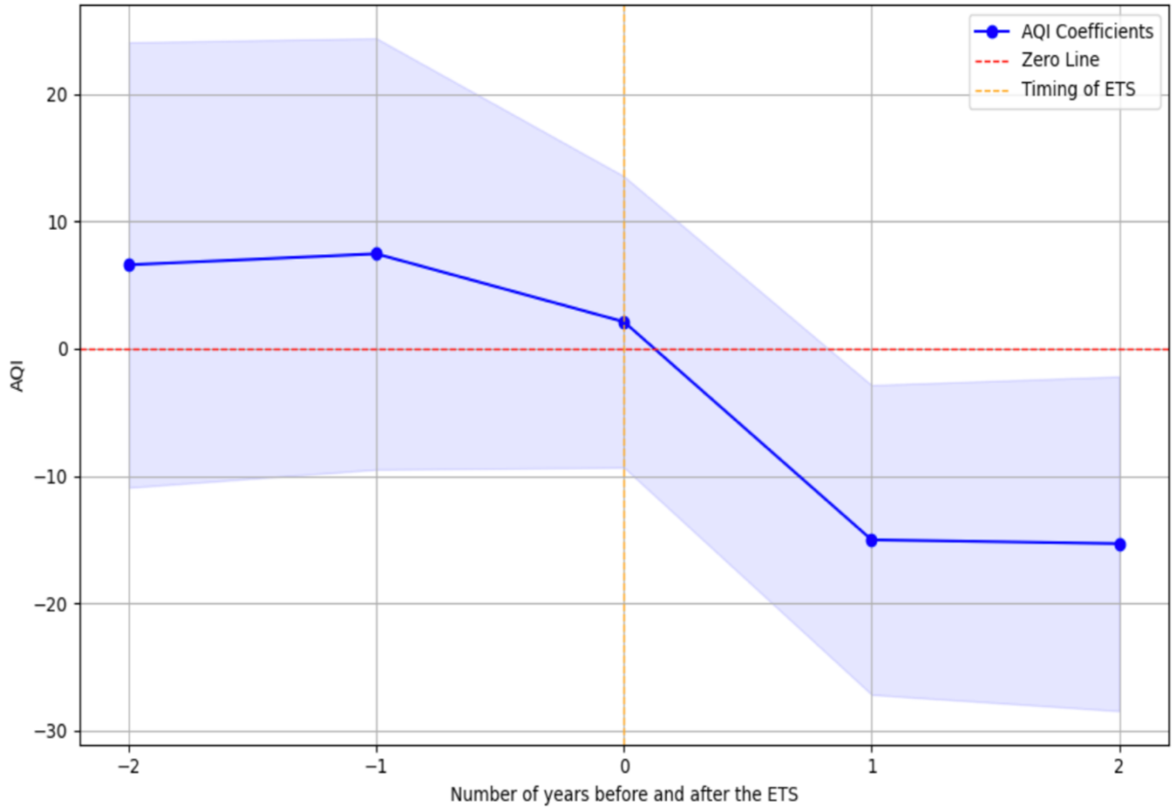
I conducted the event study analysis to ensure the results were robust. There is potential that there is pre-existing factors in the carbon emissions trends to obtain results on the distinct changes between the pilot and non-pilot areas. I conduct a parallel trends analysis for AQI, using Fujian province as the treatment group(Figure 15) and other provinces and cities that implemented the ETS as the treament group(Figure 16) separately. The orange dotted line indicates the start of the ETS implementation, and the red dotted line represents the zero line. The blue shaded area represents the 95% confidence interval. When using Fujian as the treatment group, the analysis covers the period from 2013 to 2018. For all the cities as the treatment group, the analysis spans 2 years before and after the ETS implementation due to varying implementation times across different locations. From the chart, we can see that before the implementation of the ETS, the 95% confidence intervals for the treatment and control groups include zero. However, after the ETS implementation, there is a sharp decline, indicating that the ETS has led to a decrease in AQI and thus an improvement in air quality.

Figure 15. Parallel Trends Test for AQI - Fujian Province(Treatment Group)



Notes: This analysis spans from 2013 to 2018. Fujian Province is treatment group. All other provinces that never implemented ETS are control group. Fujian implemented ETS in December 2016.

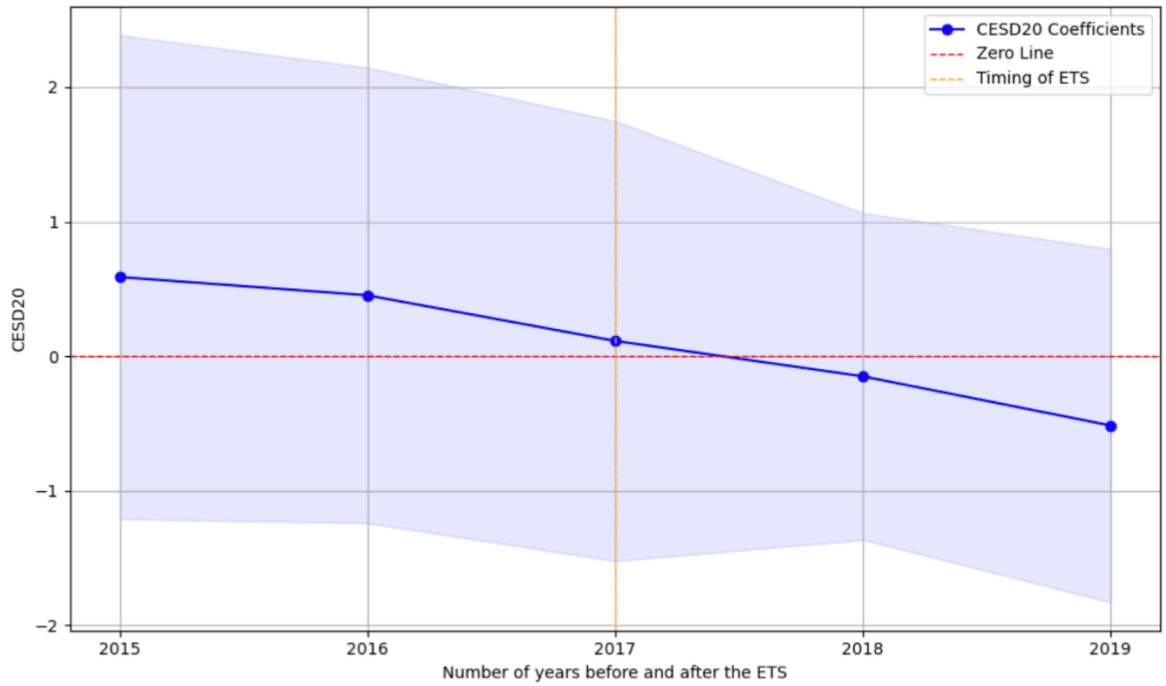
Figure 16. Parallel Trend Test for AQI - All 7 Provinces (Treatment Group)



Notes: This analysis spans from two years before and after the implementation of ETS. Province and places that implemented the ETS before 2016 are treatment group. All other provinces that never implemented ETS are control group.

I also conducting a parallel trends analysis for mental health, comparing Fujian province as the treatment group to other provinces and cities that implemented the ETS. I use CESD20 score to represent people's mental health. The analysis covers the period from 2013 to 2018. From the chart, we can see that before the implementation of the ETS, the 95% confidence intervals for the treatment and control groups include zero. However, after the ETS implementation, there is a sharp decline, indicating that the ETS has led to a decrease in CESD20 and thus an improvement in mental health.

Figure 17. Parallel Trends Test for CESD20 - Fujian Province(Treatment Group)



Notes: This analysis spans from 2015 to 2018. Fujian Province is treatment group. All other provinces that never implemented ETS are control group. Fujian implemented ETS in December 2016.

3.6.4 Robustness Checks

In the previous context, I set up two scenarios. The first involved using Fujian Province as one treatment group and provinces without Emission Trading System (ETS) policies in both 2013 and 2016 as the control group. The second scenario included provinces that implemented ETS in 2013 and 2016 as the treatment group, with provinces without ETS policies in both years as the control group. However, considering the potential spillover effects of air quality between provinces, where the air quality of one province might be influenced by neighboring provinces due to wind patterns.

For the robustness check, two additional analyses were conducted, each excluding neighboring provinces to assess the impact of ETS on air quality in a more localized context. This approach ensures a more accurate assessment of the impact of ETS on air quality by minimizing the influence of neighboring provinces implementing similar policies. By doing so, it provides a comprehensive understanding of the effectiveness of ETS in improving air quality across different regions.

When neighboring provinces are excluded, I observe roughly similar results: significant decreases in AQI, PM2.5, and PM10, indicating a notable improvement in air quality. However, compared to not excluding neighboring provinces, I find that the impact of ETS becomes more pronounced when they are excluded. For instance, when Fujian Province is taken as the treatment group, without excluding neighboring provinces, AQI decreases by 10.98, whereas when neighboring provinces are excluded, the decrease is 11.13. This suggests that ETS policies indeed have a positive impact on the air quality of neighboring provinces as well.

Both analyses, despite different treatment group compositions, consistently demonstrate the substantial positive impact of ETS on air quality when neighboring provinces are excluded from the analysis. These findings further underscore the robustness of the relationship between ETS implementation and improved air quality, even in more localized contexts.

Table 20. ETS Impact on AQI, $PM_{2.5}$, and PM_{10} When Have One Treatment and Exclude Neighbors

	(1)	(2)	(3)
	AQI	$PM_{2.5}$	PM_{10}
ETS*Post	-11.13***	-8.28***	-14.31***
	(2.36)	(1.63)	(2.78)
Province F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
N	982,726	982,726	982,726
R^2	0.1122	0.1314	0.0711
Adj. R^2	0.1122	0.1314	0.0711

Notes: Standard errors are clustered by province and in parentheses. Statistical significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 21 ETS Impact on AQI, $PM_{2.5}$, and PM_{10} When Have More Treatments and Exclude Neighbor

	(1)	(2)	(3)
	AQI	$PM_{2.5}$	PM_{10}
ETS*Post	-12.25***	-8.62***	-15.81***
	(2.36)	(1.63)	(2.78)
Province F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
N	971,530	971,530	971,530
R^2	0.1122	0.1314	0.0711
Adj. R^2	0.1122	0.1314	0.0711

Notes: Standard errors are clustered by province and in parentheses. Statistical significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.7 Conclusion

In this study, I employed the DID method to evaluate the effects of the Emission Trading System on both air quality and mental health. The findings demonstrate a significant enhancement in air quality subsequent to the implementation of ETS, evidenced by reductions in AQI by 10.98 units, PM2.5 by 7.92 ug/m3, and PM10 by 13.23 ug/m3. Furthermore, consistent results were obtained when expanding the treatment group to include more provinces and excluding neighboring provinces from the control group.

Additionally, the analysis indicates that individuals residing in Fujian Province experienced a notable decrease of 1.1115 in mental health scores following the introduction of ETS, suggesting a positive impact on mental well-being.

I also tested the parallel trends assumption and found similar trends between the treatment and control groups before the implementation of the Emission Trading System (ETS). However, following the implementation, both AQI and CESD-20 scores showed reductions, indicating that ETS indeed improves air quality indeed improve air quality and mental health.

Appendices

Appendix A. Chapter 2 Supplementary Figures

Figure A 1. Event Study Analysis for AQI

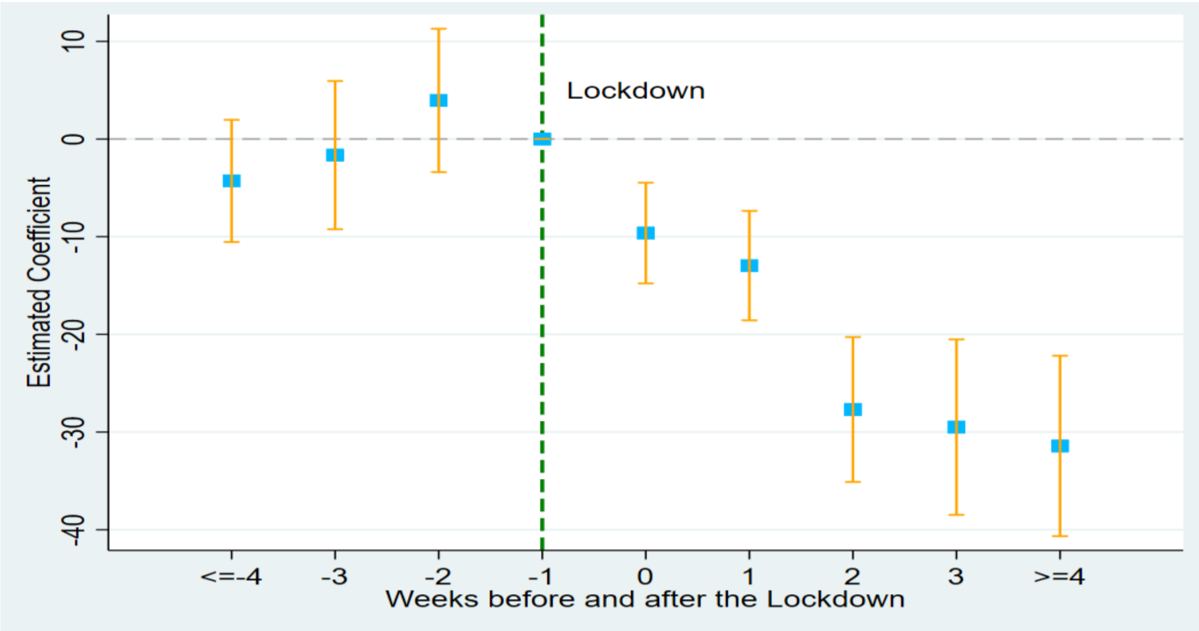


Figure A 2. Event Study Analysis for PM10

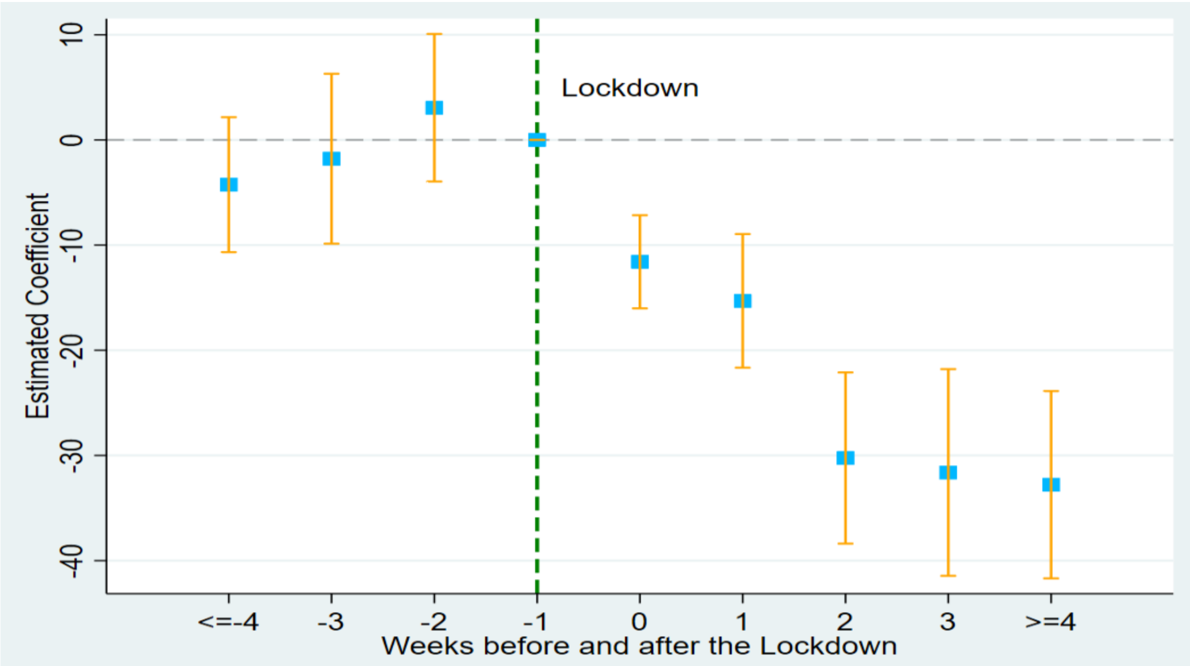


Figure A 3. Event Study Analysis for SO2

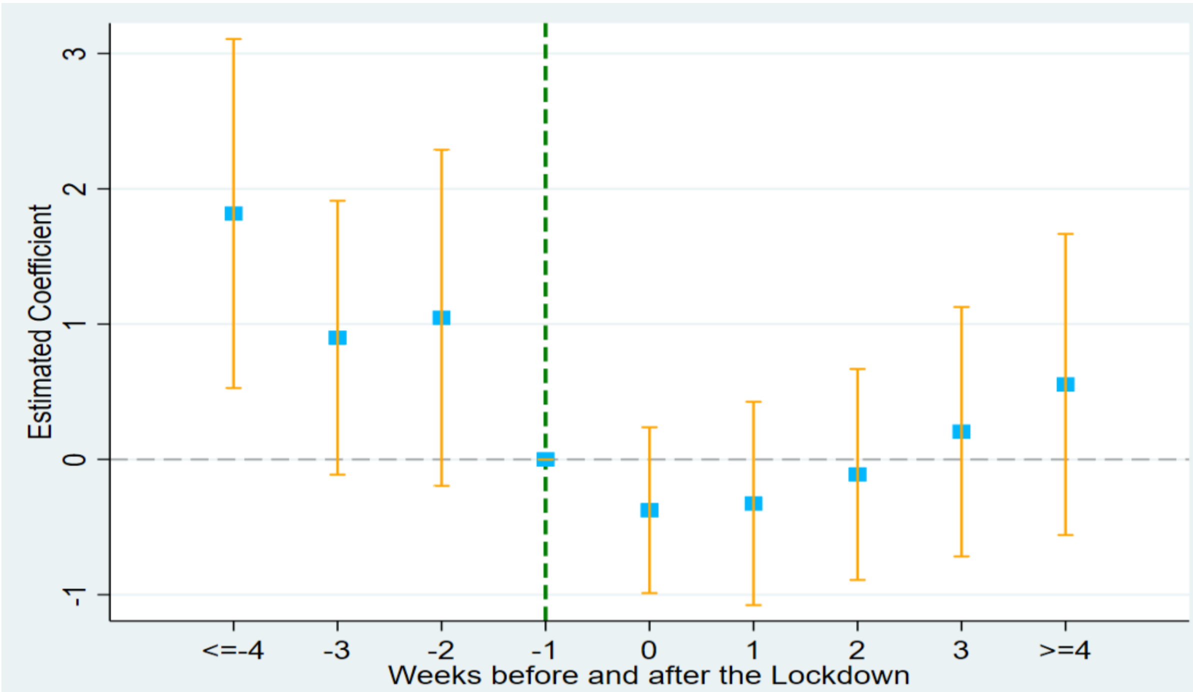


Figure A 4. Event Study Analysis for NO2

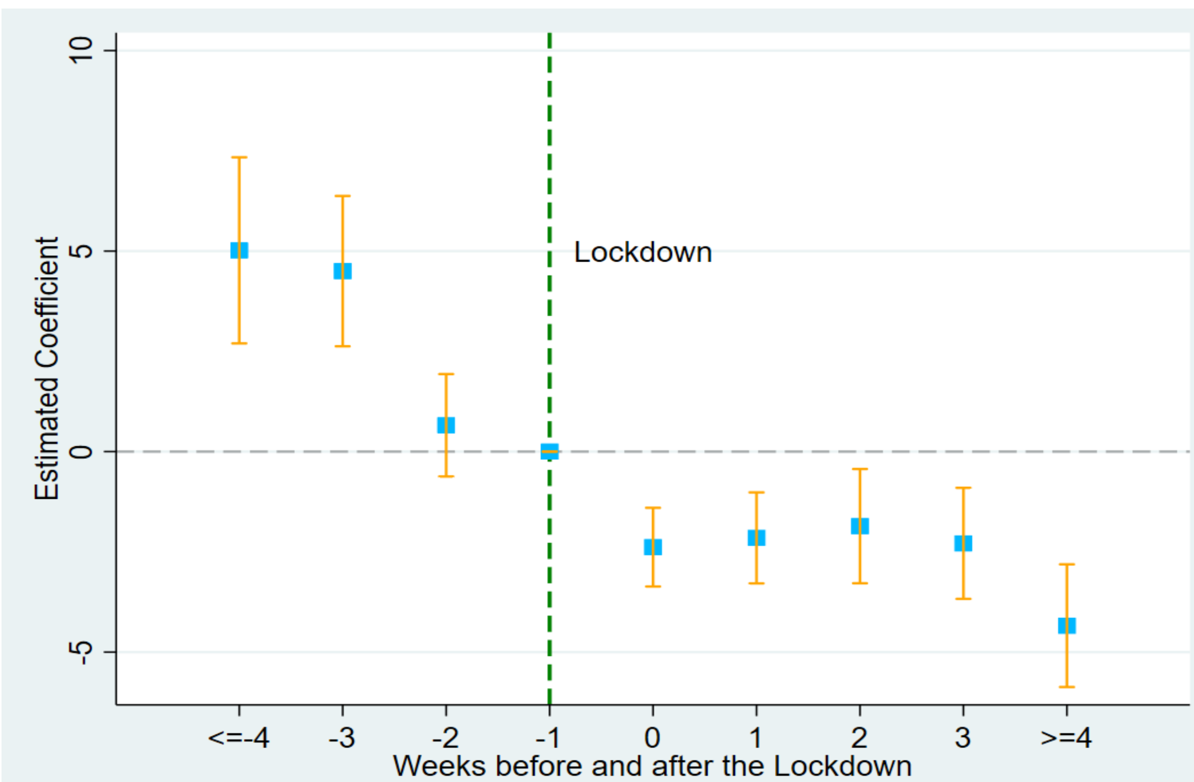


Figure A 5. Event Study Analysis for CO

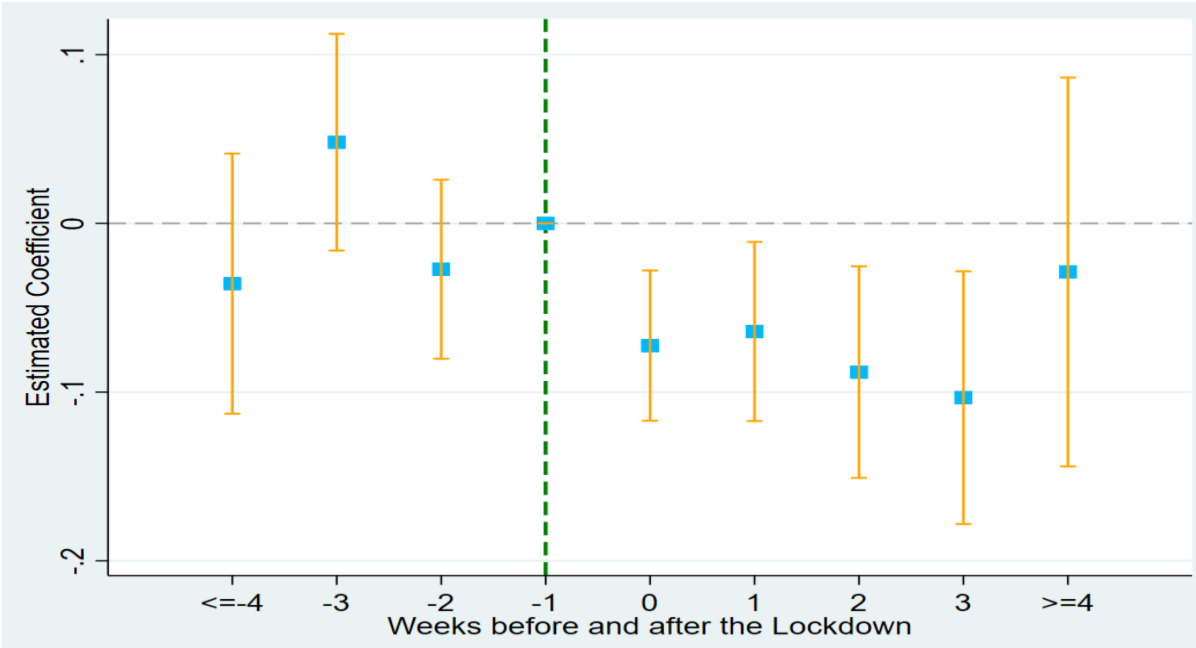
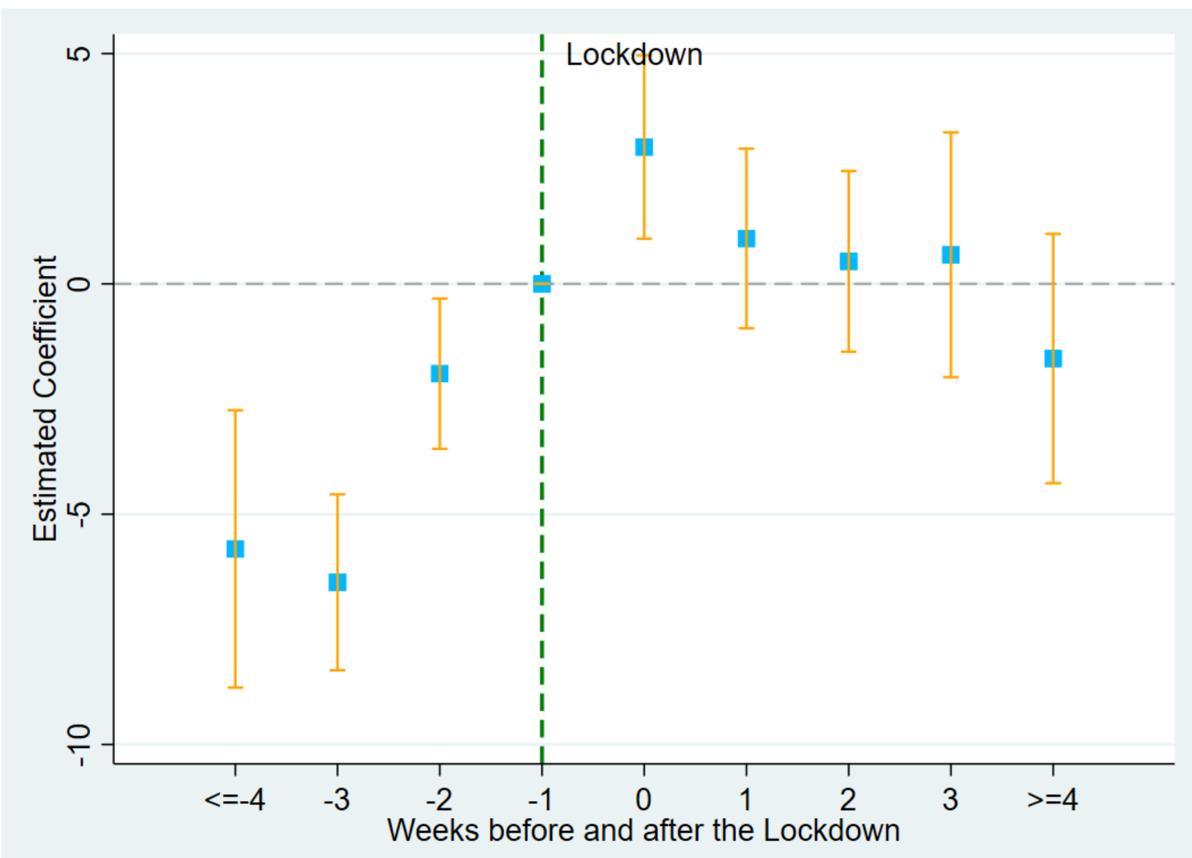


Figure A 6. Event Study Analysis for O3



Appendix B. Chapter 3 Introduction on CESD Score

In CFPS 2016, the Center for Epidemiologic Studies Depression Scale (CES-D) is used to test an individual's level of depression. This set of scales has many forms. In CFPS 2012, it uses a scale containing 20 questions which were called CESD20. However, the feedback from the field survey shows that the scale used in CFPS personal questionnaire seems to have too many questions. The acceptance level of interviewees is not high. Therefore, in CFPS2016, they adjusted the design and switched to the simplified model of this set of scales. The number of questions was reduced from 20 to 8 questions. At the same time, in order to effectively compare the depression scores between different rounds, they chose face-to-face interviews and select 1/5 samples in the population randomly to use CESD20, and the remaining 4/5 samples use CESD8. Based on this design, the data processors performed equivalent operations on the scores of the two set of questions in the later stage, and the method used was the percentile equalization method (equipercentile equating), resulting in a comparable score CESD20SC (constructed CESD20 total score). This score of CESD20 is maintained, which is also comparable to the score of CESD20 scale in CFPS2012. In addition to comprehensive variable scores CESD20sc, the datasets also retain the original single-item scores.

The 20 questions include:

_____ 1. You will be troubled by things that you didn't care about before.

_____ 2. You don't want to eat and your appetite is bad.

_____ 3. Even with the help of family and friends, you can't get over your bad mood.

_____ 4. You feel that you are as good as everyone else. (×)

_____ 5. When you are doing things, you often cannot concentrate.

_____ 6. You feel depressed.

_____ 7. You find it very difficult to do anything.

_____ 8. You are full of hope for the future. (×)

_____ 9. You see yourself as a failure in your past life.

_____ 10. You feel fear.

_____ 11. You do not sleep well.

_____ 12. You are very happy. (×)

_____ 13. You talk less than usual.

_____ 14. You feel lonely.

_____ 15. You feel that people are unkind to you.

_____ 16. You enjoy life. (×)

_____ 17. You often cry for no apparent reason.

_____ 18. You feel sad.

_____ 19. You feel that people don't like you.

_____ 20. You feel like you can't make progress.

The choices for those questions are:

0: Hardly ever (less than a day)

1: Rarely (1-2 days)

2: Often (3-4 days)

3: Almost always (5-7 days)

To calculate the depression points, two steps are needed. Step 1: The scores for items 4, 8, 12, and 16 [namely marked with (×)] take the opposite score, that is, if you mark 0 points on one of the items, then In fact, it is 3 points; in the same way, change 1 point to 2 points, change 2 points to 1 point, and change 3 points to 0 points. Step 2: The scores of these 4 items are the converted scores, and then add up all the scores for all 20 questions.

It can be seen that the lowest score may be 0 points, and the highest score may be 60 points. Psychologists set 16 points as the dividing line between depressed people and non-depressed people. Depression is usually divided into three types: mild depression (16-20 points), moderate depression (21-25 points), and severe depression (25-60 points). It is worth mentioning that the depression scale is different from the happiness scale, and this score is particularly closely related to your mood and usual mental state. So, you might get different numbers for depression when you measure it over different time periods; even two weeks apart, the results can be different.

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