ESSAYS ON NATURAL DISASTER AVERSION

By

Pei-Jyun Lu

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food, and Resource Economics – Doctor of Philosophy
Environmental Science and Policy – Dual Major

2024

ABSTRACT

Natural disasters cause significant economic losses and death tolls worldwide. In the United States alone, weather-related disasters have cost over $2.5 trillion in the past four decades, with increasing severity over time. Governments implement disaster risk reduction policies to mitigate these impacts by promoting avoidance behaviors, reducing exposure, and minimizing damage to people, crops, and property. However, critical questions remain understudied: Do these policies effectively reduce weather-related impacts? How can their efficacy be evaluated? What drives governments to terminate ineffective policies? This dissertation addresses these questions and provides insights for policymakers.

The first chapter, "*Tropical Cyclone Day-Off Orders, Warnings, and Avoidance Behavior*," examines Taiwan's day-off policy during tropical cyclones, which allows residents to avoid exposure to strong winds, landslides, and flooding. Using transportation data as a proxy for avoidance behavior, the analysis reveals that while mandatory day-off orders reduce exposure, people may take similar actions even without them. Comparing Taiwan with Miami-Dade County, Florida, the study finds similar avoidance patterns in areas without mandatory orders. These findings suggest that providing reliable information may allow individuals to make informed decisions, reducing unnecessary disruptions.

The second chapter, "*Efficacy Analysis of Cloud Seeding Programs in Kansas Agriculture*," evaluates cloud seeding as a hail suppression strategy for protecting crops in Kansas, a state prone to severe hailstorms. The findings show that cloud seeding reduces hailstorm intensity but does not significantly lower crop loss ratios, as hailstones remain large enough to cause damage. Additionally, cloud seeding unintentionally increases flood-related crop losses and exhibits spillover effects, reducing downwind counties' sorghum productivity. Despite a positive net present value overall, these spillover effects lead to negative net present value in downwind counties, complicating the program's cost-benefit profile.

The third chapter, "*Factors Influencing Policy Termination: The Cloud Seeding Program in Kansas*," investigates the determinants of policy termination using Kansas' cloud seeding program as a case study. Analysis reveals that counties experiencing higher hail-induced crop losses are more likely to terminate the program, reflecting its perceived

inefficacy. Furthermore, neighboring counties' termination decisions delay the termination process, aligning with diffusion theory, which posits that governments learn from neighbors’ experiences. This study highlights the role of inefficacy and policy diffusion in driving termination decisions.

In conclusion, this dissertation explores the effectiveness and sustainability of disaster risk reduction policies through the lens of two case studies: Taiwan’s tropical cyclone day-off orders and Kansas’ cloud seeding program. The findings emphasize the importance of rigorous evaluation to improve policy design and highlight the need for continued research into innovative risk reduction strategies to enhance resilience against natural disasters.

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my advisor, Professor Mark Skidmore, whose guidance, encouragement, and support made this work possible. His insights and mentorship have been invaluable throughout all stages of my Ph.D. journey, shaping both my research and personal growth. I am profoundly grateful for his patience, belief in my abilities, and commitment to my success.

I would also like to extend my heartfelt thanks to my committee members for their brilliant comments and suggestions, which have enriched my work. Their expertise and feedback provided me with clarity and direction, helping me refine my research.

A special thanks goes to my family and friends, whose understanding and support sustained me throughout this journey far from home. Their unconditional love and trust gave me the strength to persevere during challenging times.

Finally, I am grateful to the Taiwanese government for providing a doctoral scholarship, without which this work would not have been possible.

To everyone who contributed to this journey, my sincerest thanks.

TABLE OF CONTENTS

INTRODUCTION

Natural disasters result in substantial economic losses and significant death tolls globally. In the United States alone, the total costs of weather-related disasters have exceeded $2.5 trillion over the past four decades. Additionally, there is a noticeable trend of increasing severity in these disasters.

According to the IPCC (2012), weather-related risk encompasses three interrelated components: hazardous events, exposure, and vulnerability. If any one of these components is absent, the risk does not exist. For instance, a landslide is a powerful natural disaster, but if no residents or properties are located in the potential affected area, the probability of landslide risk is nearly zero. Based on this framework, governments are implementing disaster risk reduction policies to help people take aversion or avoidance actions and mitigate adverse impacts on human beings, crops, and properties from these three perspectives.

However, do these policies effectively reduce weather-related impacts? How can we evaluate the efficacy of risk reduction policies? How do governments decide to terminate ineffective policies? Additionally, what are the determinants of these decisions? These questions are critical but understudied. Therefore, the goal of this dissertation is to explore and shed light on these questions and provide insights for future policymakers.

In the first chapter, titled "*Tropical Cyclone Day-Off Orders, Warnings, and Avoidance Behavior*," I investigate the avoidance behaviors of the day-off policy in Taiwan for reducing exposure to tropical cyclones. On average, four tropical cyclones make landfall in Taiwan each year, causing significant damage. To protect people from tropical cyclones, the government announces mandatory day-off orders, which allow residents to stay home, avoiding work and school to reduce exposure to strong winds, landslides, or flooding. However, this policy is controversial. Governors may announce a day-off, but the tropical cyclones might not reach Taiwan due to its unpredictability, causing unnecessary interruptions to businesses and schools. Instead of conducting surveys as previous literature has done, I used transportation data to explore people's responses to these mandatory orders. Given that the public transportation system in Taiwan is mostly underground, reliable, and operational during tropical cyclones, a decrease in passenger numbers would explicitly imply that people are not going to work or school, capturing their avoidance behavior. The results indicated that people do respond to the government's day-off order. However, they might take similar actions even without the mandatory order. Due to data limitations, I compared the situation with another hurricane-prone area, Miami-Dade County in Florida, and found that the pattern of avoidance behavior is similar without a mandatory order. Based on these findings, governments might consider providing information and allowing individuals to make avoidance decisions according to their temporal and spatial situations.

Besides reducing exposure to natural disasters, it is rarely discussed how to adopt policies to reduce hazardous events themselves. This is largely due to the fact that most natural disasters, such as earthquakes, are difficult to predict or too powerful to control. In the late 1940s, scientists began exploring a new field of earth engineering: cloud seeding. Their initial experiments aimed to reduce the intensity and alter the direction of hurricanes in the Gulf region. However, these experiments did not achieve their goals. Consequently, after the 1970s, scientists shifted their focus from modifying hurricanes to hail suppression and rain augmentation.

In the second chapter, titled "*Efficacy Analysis of Cloud Seeding Programs in Kansas Agriculture*," I delve into the implementation of cloud seeding and evaluate its effectiveness in Kansas. This state is a leading producer of winter wheat, corn, and sorghum, but these crops are threatened by extreme hailstorms every growing season. Recognizing the local need, the government has sponsored experimental fees and provided financial support to implement cloud seeding. However, the efficacy of hail suppression remains contentious, and the spillover effects in the context of hail suppression have not been thoroughly discussed in the literature. In this chapter, I found that cloud seeding reduces the magnitude of hailstorms. However, the average size of hailstones after treatment still exceeds the threshold size that causes damage. Consequently, cloud seeding does not statistically significantly reduce crop loss ratio due to hail. Additionally, I discovered that cloud seeding unintentionally increases flood-related crop loss ratio, likely due to the concentration of rainfall within a short time window. Furthermore, the results indicate that the spillover effect of cloud seeding exists: downwind areas experience productivity losses in sorghum production, though there is no significant effect on precipitation. Finally, I provide a cost-benefit analysis in the chapter. Overall, in Kansas, the net present value of the cloud seeding program in terms of crop productivity is positive. However, it is not a win-win situation for all counties. When considering downwind counties that experience the spillover effect, the net present value of the cloud seeding project turns negative.

In Kansas, despite significant subsidies and positive net present value overall, local governments decided to terminate the cloud seeding program. Conversely, in Taiwan, there are frequent debates whenever local governments announce a day-off order due to an approaching tropical cyclone that does not ultimately reach the island. People have submitted proposals to terminate the day-off order to the National Development Council in Taiwan, but these proposals have not garnered enough votes to pass.

In the third chapter, titled "*Factors Influencing Policy Termination*," I review the policy termination theory and examine the determinants that led to the termination of the cloud seeding program in Kansas. Local governments in Kansas annually decide whether and how much to sponsor the cloud seeding program. Initially, I profiled the counties that participated in the cloud seeding program, highlighting characteristics such as frequent hailstorms, higher support rates for the Republican Party, and greater numbers of neighboring counties also involved in the program. This profile characterizes a cluster of counties in Western Kansas, where higher elevations expose them to significant hailstorm risks. I further explored the determinants influencing the termination of the cloud seeding program in Kansas. The results indicate that counties experiencing higher crop loss ratios due to hail in previous years were more likely to terminate the cloud seeding program. This finding underscores the perceived inefficacy of the cloud seeding efforts in mitigating hail damage for these counties. Additionally, the termination decisions of neighboring counties delayed the decision-making process of observed counties. According to diffusion theory, counties' decisions are influenced by their neighbors through a learning process, where counties gather information from neighboring experiences before making their own decisions.

In conclusion, this dissertation explores the complex realm of disaster risk reduction policies, focusing on both exposure and hazard reduction strategies. The research aims to reveal the factors that influence the efficacy and termination of these policies, drawing insights from case studies such as Taiwan's day-off orders and Kansas' cloud seeding program, contributing to a deeper understanding of how such policies unfold in practice.

CHAPTER 1: Tropical cyclone day-off orders, warnings, and avoidance behavior

I. Introduction

Tropical cyclones, also known as hurricanes and typhoons, are regional extreme weather phenomena that result in fatalities and tremendous economic losses every year. Over the past five decades, tropical cyclones have resulted in more than 1,945 disasters, $1.4 trillion (USD) in economic losses, and approximately 780,000 deaths worldwide, according to World Meteorological Organization[1]. To mitigate fatalities and losses, governments play a crucial role in assisting residents in taking action to avoid harm during tropical cyclones. Governments provide information and guidelines and may also issue mandatory orders to compel people to take protective measures, such as evacuating hazardous areas due to flood risk. These avoidance behaviors, wherein people take action to reduce their disaster exposure, help to mitigate potential harm and damages (Dickie, 2017). However, the effectiveness of government-issued mandatory orders in influencing individuals' avoidance behavior during tropical cyclones remains underexplored. This research aims to address this gap in the literature and offer new insights for policymakers considering similar risk reduction strategies.

In Taiwan, since 1980 the government has issued typhoon day-off orders to facilitate avoidance behavior. This policy mandates a day off from work and school to either stay put or evacuate from dangerous areas. Similarly, in the United States (US), governments issue mandatory evacuation orders to prompt citizens to take protective measures in response to hazardous events, including flooding and wildfires. However, such mandates are potentially controversial due to the inherent uncertainty in accurately anticipating exposure. For instance, the route of a tropical cyclone is unpredictable within a short time horizon. When risk averse government officials make decisions as tropical cyclones approach, they tend to make more precautionary decisions, leading to an over reliance on mandatory orders, resulting in higher socio-economic costs (Hausken, 2021). For example, the mandatory evacuation from Hurricane Rita led to approximately 100 traffic-related deaths. In this article, I examine the degree to which people engage in avoidance behavior in response to mandates versus the provision of information/guidance without mandates.

Most of the literature on avoidance behavior examines taking actions to prevent

[1] See https://wmo.int/topics/tropical-cyclone.

temporal or permanent health damage, such as reducing exposure to heatwaves, air pollution, and water contaminants (Dickie, 2017; Sheldon and Sankaran, 2019; Kim, 2021). Within the context of tropical cyclones, the key literature discusses optimal evacuation decisions, including route selection and the timing of evacuation order announcements, with the goal of informing government evacuation plans.

Regarding individual behavior, Whitehead (2005) conducted several surveys to learn about contingent hurricane evacuation decisions, such as when and how to evacuate hazardous zones during hurricanes. Although surveys can provide detailed and micro-level data, they are expensive and time-consuming. Moreover, people may forget details over time or experience trauma, leading to recall errors.

Rather than conducting surveys to obtain information on individual behavior, some researchers have used aggregate data to investigate avoidance behavior over longer time periods. For example, Neidell (2009) examined avoidance behavior in relation to attendance at public facilities when people receive air quality information. Moretti and Neidell (2011) utilized marine transportation data to measure avoidance behavior in the context of air pollution. Similarly, Sheldon and Sankaran (2019) used aggregate electricity usage data to investigate avoidance behavior in Singapore during Indonesian forest fires. Finally, Rabassa et al. (2021) analyzed bike-sharing data in Buenos Aires to investigate avoidance behavior when people receive heatwave alarms, showing that those with greater vulnerability are more aware of the alarms.

Moreover, access to critical information may influence averting behavior. Lack of sufficient information increases vulnerability due to false or inaccurate risk perceptions (IPCC, 2012). False risk perceptions in turn lead to gaps between hazardous events and the severity of the consequences, resulting in insufficient averting behavior (Thompson and Dezzani, 2021). In the context of tropical cyclones, empirical evidence shows that individuals who have experienced previous storm evacuations tend to evacuate half a day earlier upon receiving subsequent evacuation orders (Jiang et al., 2022). Information quality is also discussed, including how to make critical evacuation decisions in the presence of a high level of uncertainty (Kailiponi, 2010), as well as comparing how people respond to detailed information versus a simple warning (Dormandy et al., 2021). Finally, Beatty et al. (2019) employed supermarket scanner data in the US to investigate consumer responses to government advice on tropical cyclones.

To my knowledge, there are no studies that utilize aggregate data to investigate avoidance behavior in the context of tropical cyclones, nor is there research examining how people respond to alarms. In this chapter, I utilize metro system transportation usage data to examine tropical cyclone avoidance behavior in two major tropical cyclone regions worldwide: Taipei City and Kaohsiung City in Taiwan, as well as Miami-Dade County in the United States. Ideally, my examination would entail an event study to examine behavior before and after the adoption of the day-off order policy in Taiwan, but data constraints prevent such analyses. I therefore examine transportation usage patterns in different regions with different disaster policies to learn more about disaster aversion behavior in two policy regimes. I think the cases of Taiwan and Florida are comparable for several reasons.

First, both regions experience a similar frequency of tropical cyclones in a year, with at least two storms annually over the past few decades. Additionally, they employ identical criteria for categorizing the intensity of tropical cyclones, enabling us to identify storms of similar scales in the two regions. Second, both regions face similar threats from tropical cyclones, such as flooding from storm surges and riverine floods, as well as flying debris from strong wind gusts. Consequently, government authorities in each region have implemented disaster avoidance policies. In Taiwan, the day-off order requires individuals to either stay in place or evacuate from hazardous areas. Similarly, the Florida state and local governments may issue a mandatory evacuation order, which implies a day-off for residents living in evacuation zones. In other words, businesses have no right to require workers to work in the evacuation zones under a mandatory evacuation order. However, compared to Taiwan, Florida issues mandatory orders less frequently, which provides an opportunity to identify tropical cyclones of similar magnitudes and observe behavior in the two regions with and without mandatory orders.

Additionally, both regions share similar environmental conditions and demographic variables. For example, their average temperatures and precipitation levels are comparable (refer to the summary statistics in Section 3, Table 3). Both areas have populations of over 2.6 million, with Kaohsiung City having 2.8 million residents and Miami-Dade County having 2.7 million residents. Finally, the usage rate and customer demographics of the public transportation systems are also similar. Approximately 5% of the population in both cities rely on the public transportation system as their primary means of transportation. The behaviors associated with public transportation usage are also similar; for instance, the main age group falls between 16 and 34 years old, and the primary purpose for using public transportation is commuting between home and work.

Moreover, according to a survey conducted by the Miami-Dade Transportation Planning Organization (2018), over 80% of people who choose to use public transportation in Miami-Dade County have access to an automobile. The distributions of household income among transit users were consistent with household income distribution in Florida[2]. For example, only 8% of public transportation users in Miami-Dade County have a household income of less than $25,000 annually, compared to 10.7% of the population in Florida. Therefore, the transportation data does not disproportionately represent the low-income population or those without access to a car who rely on public transportation in the region.

This article offers several contributions to the literature on disaster aversion. First, to the best of my knowledge, this article is the first to discuss how people respond to government-mandated day-off orders. My analysis demonstrates that people do respond to government orders by engaging in avoidance behavior. Second, this article adopts a different approach to studying avoidance behavior. In this literature, survey-based research is the more common approach to investigate avoidance behavior in the context of tropical cyclones. In this article, I also use aggregate transportation data to analyze responses to information without government mandates. Third, I provide case studies from two regions and compared people's responses under mandatory orders versus information-only schemes.

[2] According to the United States Census Bureau, household income distribution in Florida in 2022 is as follows: 10.7% earn less than $25,000, 19.7% earn between $25,000 and $49,999, 17.4% earn between $50,000 and $74,999, 13.4% earn between $75,000 and $100,000, and 33.2% earn above $100,000. (see: https://data.census.gov/table/ACSST1Y2022.S1901?q=Florida%20Income%20and%20Poverty). According to the Miami-Dade Transportation Planning Organization (2018), survey results show that annually, 8% of households earn less than $25,000, 20% earn between $25,000 and $49,999, 20% earn between $50,000 and $74,999, 18% earn between $75,000 and $100,000, and 34% earn above $100,000.

The paper proceeds as follows. Section II provides background on Taiwan and Miami's cyclone policies, section III describes the data, section IV describes the empirical approach, section V presents the results, and discussions with conclusions are presented in section VI.

II. Background

Taiwan is a hot spot of natural disasters in the world (World Bank, 2005). In total, 73.1% of the Taiwan territory and 73.1% of the population are threatened by more than four kinds of natural disasters. Also, almost 95.1% of the population in the country was at a high mortality risk from more than three kinds of natural disasters. Among all types of natural disasters, typhoons and earthquakes cause tremendous economic loss and fatalities in Taiwan. For example, the earthquake that occurred on September 21, 1999 resulted in 2,415 deaths and 11,305 people who were severely wounded. The total economic loss was $11.2 billion. In 2009, Typhoon Morakot caused 644 fatalities, 1,555 people who were severely wounded, and $3.4 billion economic losses, which was 0.91% of GDP (NCDR, 2011).

On average, four typhoons make landfall in Taiwan every year with strong wind is the main cause of damage. However, even though some typhoons only pass by Taiwan without a direct hit, they may come with a southwesterly flow[3]. Sometimes several typhoons pass by together and cause the Fujiwara effect. In those two situations, severe precipitation occurs within a very short period (i.e., 24 or 48 hours), triggering landslides, storm surges, and floods.

To help limit potential damages, national and local governments provide instructions and information to the public to enable preparations before extreme weather events occur. In the case of the United States, when tropical storms approach the National Weather Service provides data on the predicted path and potential precipitation. Based on this information, state governments issue voluntary or mandatory evacuation orders. When people receive a mandatory evacuation order, they should evacuate to the designated evacuation zone. However, such orders are not enforceable. If people decide to stay in the

[3] According to Rodo and Comin (2003), "The surface wind starts in the southern Indian Ocean as a southeasterly flow, crosses the equator and becomes a southwesterly flow in the northern tropical Indian Ocean".

exposed area(s), they are responsible for their personal well-being during the storm and will not be prioritized if rescue services are needed.

For small island countries such as Taiwan, evacuation only happens in mountain areas. Staying at home is a more practical avoidance strategy for tropical cyclones for two main reasons. First, typhoons typically cover half of Taiwan's territory; thus, there is no way to evacuate the entire population at the same time as there is no safe place to go. Second, buildings in Taiwan are required to follow Seismic Building Codes and Wind Resistance Design Specifications and the Commentary of Buildings. For example, all buildings in Taipei are required to resist a maximum ten-minutes average wind speed of 42.5 meters per second. Building codes therefore provide a certain level of protection during typhoons.

Before 1980, the annual typhoon death toll was around 100. After 1980, the number dropped to 56. Injuries also decreased from 367 people (1958-1980) to 222 people (1981-2019), as shown in Figure 1. In 2009, Typhoon Morakot broke historical precipitation records and caused the second-highest number of deaths and economic loss in history of Taiwan[4]. Excluding this outlier, the average death toll and injuries during typhoons (1981-2019) were even lower at 38 and 180, respectively.

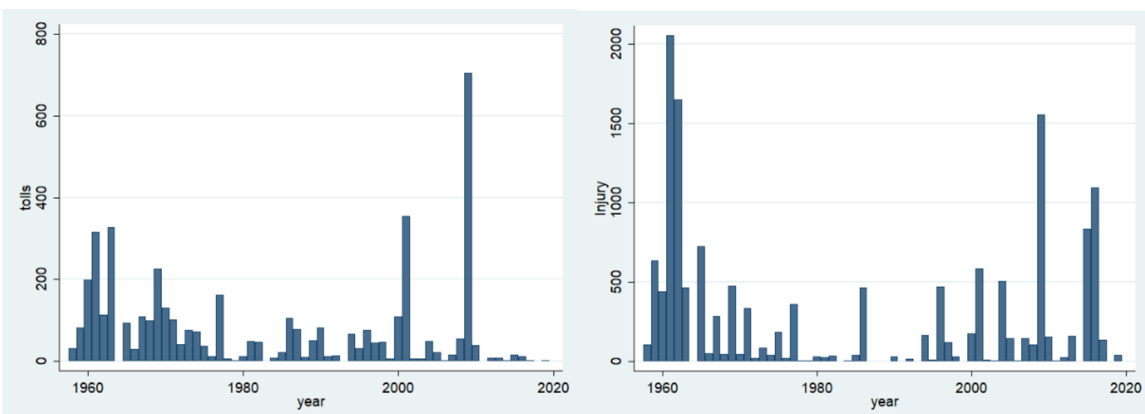


Figure 1. Tolls and Injuries during tropical cyclones in Taiwan (1958-2019)[5]

The decrease in death was coincident with the implementation of the typhoon day-off policy in the 1980s. In Taiwan, government officials announce a "typhoon day-off" when

[4] Typhoon Morakot has broken historical precipitation records, including one-day rainfall of 1,402 mm and a two-day rainfall of 2,146 mm. The two-day precipitation was even over than the thirty-year average annual precipitation. And the heavy precipitation caused a landslide in the mountain area of Kaohsiung, and 474 people dead.

[5] The data source is Ministry of the Interior, https://www.nfa.gov.tw/cht/index.php?code=list&ids=233.

a typhoon or other severe weather events occur. When officials announce the orders, the stock market is closed, and all governmental works and compulsory education classes are suspended, enabling people to stay home or evacuate from potential flood and landslide areas to designated safe places.

Between 1977 and 1993, typhoon day-off periods were announced by either the premier or the president. When a typhoon made landfall, local governments were required to report damage to the Executive Yuan. The premier considered information from the entire country and then made decisions whether to announce a typhoon day-off. For quicker disaster responses, after 1993 typhoon day-off periods were announced by the Directorate-General of Personnel Administration who referred to local weather conditions and allowed selected cities or regions (not all) to announce a typhoon day-off.

Until 2000, the Taiwan government legislated Operation Regulations on the Suspension of Offices and Classes because of Natural Disasters (henceforth referred to as Regulation). The Regulation provides objective standards for implementing a day-off, including accumulated precipitation, wind speed, landslide warning, and other factors. Currently, the Regulation authorizes local government officials to announce a typhoon day-off because local authorities have better knowledge of local conditions.

During a typhoon, the Central Weather Bureau announces typhoon warnings when typhoons approach Taiwan and provides updates every six hours, according to the Regulation. Typhoon alarms include the forecasted information on typhoons, such as wind speed, route, and precipitation. Also, typhoon alarms are announced to the public via TV, radio, and the internet. In addition to typhoon alarms, people also receive day-off orders as determined by local authorities. Typhoon day-off periods can be treated as a stronger signal.

To provide sufficient time for preparedness, the Regulation requires local authorities to announce day-off orders the day before the typhoon is expected to make landfall and no later than 10 p.m. Regarding the day-off order issuance timing, there is a trade-off between flexibility for firms and workers to adjust work schedules and the actual need for a typhoon day-off order. In general, the prediction of the typhoon path has an average of 80 to 100 km error in 24 hours. Based on available information, sometimes governments issue a typhoon day off, but the cyclone does not actually affect the target areas (i.e. counties or cities). Notably, local governments do not announce a typhoon day-off for every typhoon, but rather base decisions on forecasted weather conditions. Although typhoon day-off orders are mainly for government workers and school students, most businesses from the private sector also follow the orders, effectively making the order of broad scale and mandatory. According to the law in Taiwan, workers can refuse to go to work based on the day-off announcement. Therefore, day-off orders announced by local governments become a binding rule for businesses. This policy consistently provokes debate after tropical cyclones. In 2018, residents proposed canceling the day-off order to Taiwan's National Development Council, but the proposal did not gain sufficient support.

Overall, most people trust the Central Weather Bureau and the day-off decisions made by local government authorities, resulting in the continuation of the day-off order policy. Likewise, residents of Miami-Dade County receive information from the National Hurricane Center (NHC) through various channels, including TV, radio, and the internet. The information is updated every six hours, and different types of information are provided (as detailed in section 3.2). In Florida, when a hurricane poses a potentially life-threatening risk, the government also issues mandatory evacuation orders[6].

I hypothesize that mandatory government orders have a larger avoidance effect than warnings during tropical cyclones. In other words, I expect that a higher percentage of people will either stay at safe places or evacuate the hazardous zone when they receive a government day-off order compared to when they freely take precautions in response to government provided information and warnings. To test this hypothesis, I use data from public transportation systems to examine avoidance behaviors. When individuals receive information or mandatory orders, they may choose to remain at safe shelters or at home or evacuate from high-risk zones.

The primary purpose of public transportation is commuting to work and school. Therefore, when individuals receive a mandatory order and decide to stay at home, I expect a significant decrease in public transportation usage. During a tropical cyclone, a decline

[6] Government officials announce a storm surge map to residents, and residents can base their evacuation on the weather forecast for the zone. Normally, evacuation from a storm surge zone to a safe zone takes more than 10 hours, so the government can only announce an evacuation order based on the hurricane watch, which is the projection 48 hours in advance. Using outdated information to make these evacuation orders also caused mistakes several times in history. Furthermore, even when the government authorities announce an evacuation order, they can only encourage businesses to close earlier and allow employees to prepare earlier. It is the responsibility of residents to make an evacuation plan, including the departure time and evacuation destination. Shelters are provided only for those who have no other place to go.

in public transportation usage may indicate that aversion strategies are being taken by residents within the cyclone-affected areas.

III. Data

In this study I use data on public transportation usage, government released information, and weather to evaluate disaster avoidance behaviors. Data sources with descriptions are provided below.

(1) Public transportation data

First, the public transportation system should be reliable and continue running even during tropical cyclones to serve as a measure of avoidance behavior. In Taiwan, the metro system is essential infrastructure and provides service even when the government issues typhoon day-off orders. Similarly, in Miami-Dade County, the bus system is utilized to evacuate residents during tropical cyclones. Hence, public transportation usage information is available during tropical cyclones to measure avoidance behaviors.

Public transportation usage data can be used as a measure of the degree to which people engage in avoidance behavior during tropical cyclones. Among all transportation modes, metro system usage data in Taiwan is chosen to evaluate avoidance behavior for several reasons. First, urban traffic data, such as car flow, is limited and available only for important intersections in cities. Further, daily data is unavailable for those intersections. Second, most of the metro system in Taiwan is underground and thus strong winds and rainfall do not physically affect the service. For a small portion of the metro system that is above ground, services adjust to storms and strong winds by slowing speed and providing longer service intervals.

In this study, two different cities in northern and southern Taiwan are used to evaluate avoidance behavior by measuring differences in metro usage before, during, and after day-off orders. Daily passenger trip data for the Taipei Metro System and the Kaohsiung Metro System are obtained from the websites of Taipei Rapid Transit Corporation and the Kaohsiung Rapid Transit Corporation[7]. Data are composed of daily time series between 2009 and 2019, excluding SARS (2002-2003), the financial crisis (2007-2008), and COVID-19 (after 2020), which were major macro events that influenced willingness to use

[7] Metro systems is just a portion of public transportation, so the population used metro system was less than those percentages, see footnote 1.

the public transportation systems.

Before describing the data in more detail, there is a concern that deserves consideration. Although underground metro systems can continue operations during periods of strong wind and rainfall, flooding could still hamper the underground metro system. During the period of evaluation, the Rapid Transit Corporations addressed this problem. After typhoon Nari flooded the Taipei metro system in 2001 the Taipei Rapid Transit Corporation installed water pumps and water gates to prevent inundation during typhoons and extreme precipitation. Following the installation of water pumps and gated, both Taipei Metro System and Kaohsiung Metro System provided reliable transportation services during extreme flooding events.

For the Miami-Dade County case, transportation data come from the Department of Transportation and Public Works (DTPW), which includes information on three public transportation systems, Metrobus, Metrorail, and Metromover. The Metromover is a railway system that services a specific area in downtown Miami. Among these three means of transportation, the largest and most reliable one is the Metrobus. The bus system not only covers a broader area than the other options, but it also keeps running during hurricane events. Additionally, the DTPW also provides evacuation buses when mandatory evacuation orders are issued. Daily passenger ride data for Miami-Dade County are obtained from Miami-Dade County Public Records System[8]. Due to the data availability and avoiding the COVID period, 2015 October to 2019 December data for Miami-Dade County is used.

Although Metrobus and Metrorail are reliable transit systems in Miami Dade-County, during Hurricane Matthew and Irma the transportation services were closed for three days, which were October 6th, 2016, September 10th, 2017, and September 11, 2017. I dropped those three data points from the dataset[9].

[8] Miami-Dade County Public Records System: https://miamidadecounty.govqa.us/WEBAPP/_rs/(S(qbunqbakjua002frrxllbfbq))/SupportHome.aspx?sSessionID=

[9] The Metrobus and Metrorail service were officially recorded as closed on October 6, 2016, but in my dataset, 15,472 and 2,764 rides on Metrobus and Metrorail were recorded, respectively.

(2) Weather data

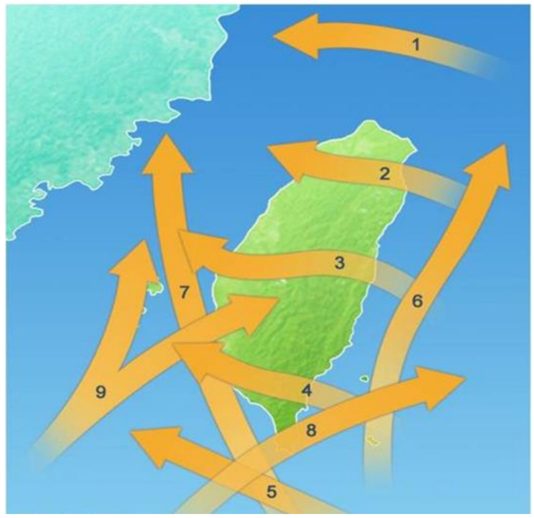
Taiwan's typhoon data come from the Typhoon Database[10], which provides information on typhoon scale, routes, event date, maximum wind speed near the typhoon center, and typhoon warnings. Typhoon routes are an important consideration in local government decision-making. If the magnitude of an incoming typhoon is severe but the predicted route is not close to a given location, then a local government will not issue a day-off order. For example, the southern city Kaohsiung issued a day-off order in 2010 for the Route 9 typhoon Lionrock, but the northern city Taipei did not. Based on historical typhoon patterns, there are ten different routes as shown in Figure 2. Route 0 means the typhoon is close to Taiwan but never makes landfall. Routes 1 to nine are the pathways that typhoons pass through Taiwan after making landfall. Route 10 is a category that collects typhoons that make landfall but do not belong to routes one to nine.

Every year many typhoons form in the Western North Pacific, but only those that impact Taiwan are included in this study. According to the Regulation, The Central Weather Bureau in Taiwan issues typhoon warnings when typhoons are within 300 km of the shoreline. These typhoons are defined as having an impact on Taiwan.

Data on historical typhoon day-off periods are collected from the website of the Directorate-General of Personnel Administration[11]. The day-off periods that only applied to specific small regions, such as communities in mountain areas, were excluded because metro systems do not cover the mountain areas. In addition, mountain areas are more fragile than cities, and people may potentially evacuate to safer places to avoid landslides. Those evacuation decisions are beyond the scope of this study.

Typhoon day-off orders and typhoon warnings are correlated with weather conditions. To control for weather conditions, I collect daily weather data from 2009 to 2019. Weather data come from the Central Weather Bureau Observation Data Inquiry System[12]. On average, each city had at least one weather station and several automatic weather stations. I use data from traditional weather stations for each city because the data from automatic weather stations do not cover the research period.

[10] Typhoon Database: https://rdc28.cwb.gov.tw/TDB/
[11] Historical day-off order: https://www.dgpa.gov.tw/en/index?mid=138
[12] Central Weather Bureau Observation Data Inquire System: https://e-service.cwb.gov.tw/HistoryDataQuery/



Source: Central Weather Bureau

Figure 2. Routes of Typhoons

The weather information in Miami includes tropical cyclone data and historical weather data. I obtain data from tropical cyclone reports from the National Hurricane Center (NHC) and Central Pacific Hurricane Center (CPHC)[13]. Similar to the Taiwan case, before a tropical cyclone makes landfall, the NHC and CPHC will announce alarms that are released on TV, radio, and the internet, providing updates every six hours. Therefore, people receive information and then decide the degree to which they will take any avoidance actions. The alarm types depend on the magnitude of the tropical cyclone, including storm surge warnings, hurricane warnings, tropical storm warnings, storm surge watch, hurricane watch, tropical storm watch, tropical cyclone public advisory, and tropical cyclone track forecast cone[14]. When a tropical cyclone watch or warning affects target areas, the NHC and CPHC will further issue a Tropical Cyclone Public advisory and update it every three hours. All the watches and warnings are issued for specific areas ranged between breakpoints, which are defined by the NHC and CPHC[15]. For studying avoidance behavior in Miami-Dade County, I first determine how many tropical cyclones affected the target areas. To do this, I count the number of times that the NHC and CPHC issued watches and warnings for the breakpoints located in Florida. From 2015 to 2019, 83 hurricanes occurred in the Atlantic, Caribbean Sea, and Gulf of Mexico areas. In total, 13 hurricanes

[13] https://www.nhc.noaa.gov/

[14] More details on: https://www.weather.gov/safety/hurricane-ww

[15] Hurricane and tropical storm watch/warning breakpoints map: https://www.nhc.noaa.gov/breakpoints/.

affected Miami-Dade County over the period of analysis.

I gather Miami historical weather data from the National Centers for Environmental Information which is funded by the National Oceanic and Atmospheric Administration (NOAA)[16]. The data includes wind speed, temperature, and precipitation. The Miami International Airport weather observation station was chosen because the station is located in the middle of the bus and railway system and is likely to better represent the weather conditions when people make decisions.

During the 2009-2019 period, 53 typhoons made landfall in Taiwan. The local government of Kaohsiung announced 27 typhoon day-off orders and 163 typhoon alarms. The local authorities in Taipei City and New Taipei City announced 23 typhoon day-off orders and 162 typhoon alarms. Table 1 shows that in Taipei and New Taipei City, fourteen and seven day-off orders occurred in moderate and severe typhoons, respectively. Kaohsiung had a pattern similar to Taipei but announced more days-off during milder typhoons. Among the data, five of ten day-off orders were implemented when typhoons came through Routes 9 and 10. Typhoons that came via Route 9 might bring heavy precipitation, and Route 10 is unexpected. In sum, people regularly receive day-off orders during moderate and severe typhoons.

Table 1. Scales of typhoon and day-off orders

Scale	Number (2009-2019)	Day-off for Taipei and New Taipei City (days)	Day-off for Kaohsiung City (days)
Mild	21	2	10
Moderate	19	14	13
Severe	13	7	4
Total	53	23	27

[16] https://www.ncdc.noaa.gov/cdo-web/datatools/selectlocation.

Sustained wind speed is the standard for classifying the scale of tropical cyclones. In Miami, the sustained wind speed between 62 to 119 kilometers per hour is called a tropical storm, and the magnitude is equivalent to a mild typhoon in Taiwan. From Table 2, the scales of hurricanes are equivalent to moderate and severe typhoons. Therefore, in my research, when I compare two different places, I examine the behavior when people receive day-off orders and hurricane alarms for tropical cyclones of similar magnitudes.

Table 2. Magnitudes of Tropical Cyclones

Taiwan		**Miami-Dade County**	
Scale	**Wind speed (km/hour)**	**Scale**	**Wind speed (km/hour)**
Mild typhoon	62-117	Tropical Storm	62-118
Moderate typhoon	118-183	Hurricane-Category 1	119-153
Severe typhoon	> 183	Hurricane-Category 2	154-177
		Hurricane-Category 3	178-209
		Hurricane-Category 4	210-249
		Hurricane-Category 5	> 249

Table 3 provides summary statistics for the variables discussed above. From Table 3, passenger trips of Kaohsiung and Miami-Dade County are around one-tenth of Taipei and New Taipei city. The precipitation data show the distribution of extreme rainfall, which often results in landslides or flooding. For example, the mean of precipitation in Kaohsiung city is 5.58 mm, and the standard deviation is around 17.8 mm. However, the maximum daily rainfall during a typhoon is 507 mm, which is almost 100 times the average.

Table 3. Summary statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Transportation (passenger trips)					
Kaohsiung Metro	4,017	157,997	39,977	23,086	472,378
Taipei & New Taipei Metro	4,017	1,793,785	362,994	150,025	3,205,325
Miami-Dade Metrobus	1,823	159,447	49,447	95	267,902
Miami-Dade Metrorail	1,550	54,167	20,869	144	88,970
Miami-Dade Metromover	1,547	21,445	6,249	0	51,690
Weather					
New Taipei-temperature (°C)	4,017	23.31	5.44	5.4	32.3
Taipei-temperature(°C)	4,017	23.58	5.5	5.6	33.2
Kaohsiung-temperature(°C)	4,017	25.71	3.9	7.9	32.0
Miami-temperature (°C)	1,826	25.63	3.48	11.1	31.7
New Taipei-precipitation (mm)	4,017	5.66	18.5	0.0	379.5
Taipei-precipitation (mm)	4,017	6.12	17.8	0.0	306.7
Kaohsiung -precipitation (mm)	4,017	5.58	23.6	0.0	507.0
Miami-precipitation	1,826	4.83	12.5	0	139.5
New Taipei-wind speed (m/s)	4,017	2.07	1.0	0.1	8.4
Taipei-wind speed (m/s)	4,017	2.43	1.2	0.4	9.6
Kaohsiung -wind speed (m/s)	4,017	2.06	0.7	0.2	10.4
Miami-wind speed (m/s)	1,824	3.53	1.4	0.9	17.2

IV. Empirical Strategy

In this section, conceptual models and empirical strategies are introduced. Also, concerning the characteristics of the time series data, several econometric tests were conducted to inform the selection of the most appropriate empirical approach.

(1) Conceptual Model

To measure the effect of the day-off policy on safety, assume the following safety production function (Neidell, 2009):

$$Safety=f(tropical\ cyclone*avoid,\ V)$$

where *Safety* measures the level of safety, such as increasing life expectancy or reducing accidents. *Tropical cyclone* includes a set of typhoon magnitude and trajectory variables, such as wind speeds, rainfall, scale, route, etc. *Avoid* includes factors that capture avoidance behavior. Interacting *typhoon* with *avoid* captures exposure to natural disaster risk, which is consistent with the risk definition noted in the introduction (IPCC, 2014). Even though a given typhoon magnitude is severe, avoidance behavior may reduce hurricane exposure. *Avoid* captures the scale of avoidance depending on the magnitude of *tropical cyclone* and other variables, such as alarms, risk perceptions, or past experiences. *V* is a vector of other behavioral and socioeconomic factors that may affect safety. For example, as mentioned in section 2, buildings should be compliant with building codes.

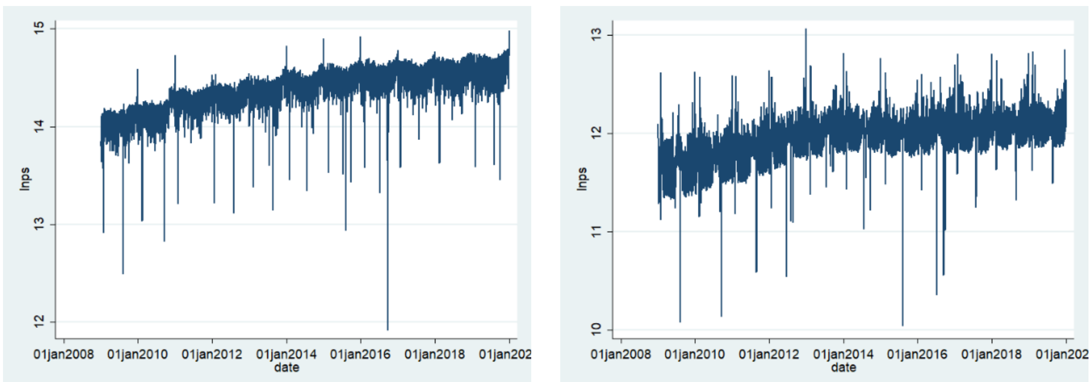
Suppose that social and environmental investments can enhance human safety. In the production function, the frequency and magnitude of hazardous events are negatively related to safety. For example, Category 5 hurricanes might reduce the life expectancy of residents in affected areas. However, avoidance behavior can mitigate the adverse effects of hazardous events. For instance, individuals may take precautions and choose to stay indoors when a tropical cyclone impacts the coastal area.

(2) Testing time-series data

Given the time-series nature of the data, stationarity is required for the regression analysis. However, in many cases time-series data are not stationary and thus may result in spurious relationships between variables (Granger and Newbold, 1974). Daily metro system passenger trips are my main data, and Figure 3 presents time trends in the data[17].

[17] I also controlled for time trends, the results of which are available in the Appendix.

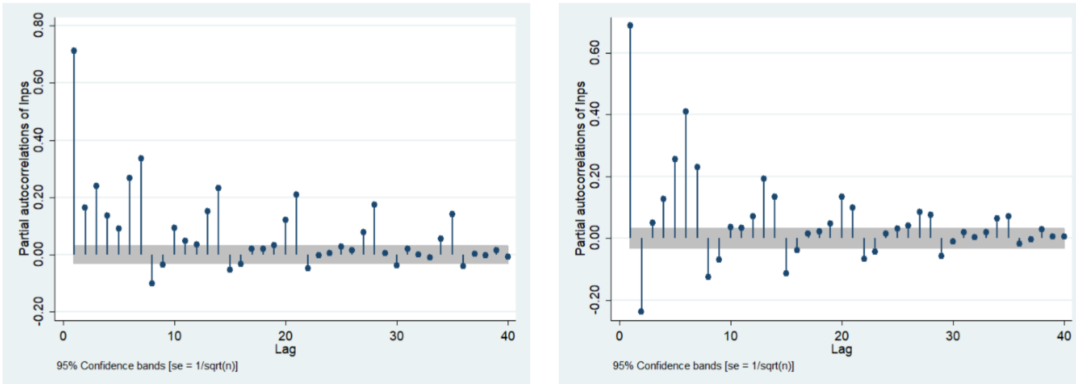
The Augmented Dicky Fuller (ADF) test is used to check the unit root. The results show passenger trips for both Taipei and Kaohsiung metro systems are stationary, which means shocks only have an impact within limited periods. I control time fixed effects in the empirical analysis, including the day of week and the month of the year, which influence passenger ride patterns. For example, the primary purpose of utilizing public transportation is commuting to work and school, so the number of passengers naturally decreases on weekends. Moreover, during the summer and winter vacations, the number of passengers also decreases.



(a) Taipei metro **(b) Kaohsiung metro**

Figure 3. Passenger trips for metro systems

When using high-frequency time-series data, there may also be serial correlation issues. I therefore conduct a Durbin-Watson test, revealing that serial correlation problems are present. Figure 4 shows the partial autocorrelations, and the autocorrelations exhibit seasonality. From the graph, seven periods (days) form a cycle and show that the metro system appears to have a weekly pattern. I include two lags of the dependent variable and adopt the Breusch-Godfrey test to check first-order and higher-order serial correlation in the errors. Including the two lags of the dependent variable removes serial correlation from the errors.



(a) Taipei metro **(b) Kaohsiung metro**

Figure 4. Partial autocorrelations of passenger trips

For the Miami Dade-county case, unlike Taiwan, Figure 5 shows decreasing time trend for daily passenger rides for the Metrobus. After the ADF test, the results show passenger rides for Metrobus, Metrorail, and Metromover are all stationary. And similarly, including two lags of the dependent variable removes serial correlation in the errors.

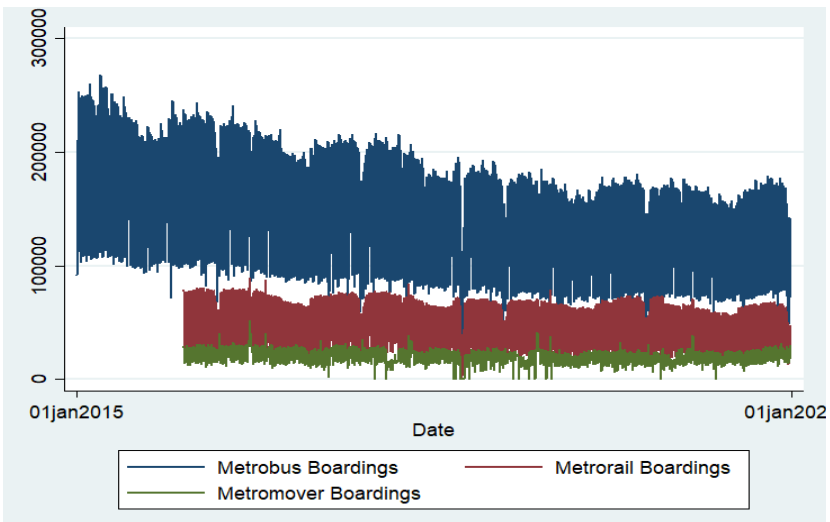


Figure 5. Passenger rides of three public transportation systems in Dade County

(3) Empirical Strategy

In the empirical analysis, I evaluate responsiveness of people to typhoon alarms. After testing and modifying the time series data as described in previous section, I employ ordinary least squares regression analysis in this study, as illustrated in Equation (1)

$$\log(PS_t) = \rho_1 \log(PS_{t-1}) + \rho_2 \log(PS_{t-2}) + \beta_1 doff_t + \gamma_1 wind_{t-1} \times route_{t-1} + \gamma_2 rain_{t-1} + \alpha_1 nholidy_t + \alpha_2 DOW + \alpha_3 MOY + \varepsilon_t \quad (1)$$

where PS_t is the total count of daily passengers in the Kaohsiung metro system from 2009 to 2019. Because the dependent variables are non-normal with an asymmetric distribution, I use the natural logarithm to approximate the normal distribution. For the Taiwan case, test how people change their behavior in response to the typhoon day-off order. To address autocorrelation in time series data (see section 3), two lags of the dependent variable, log (PS_{t-1}) and log (PS_{t-2}), are added in the regression. The independent variable $doff_t$ is a dummy variable where the value is equal to one when the government announces a day off on day t and zero otherwise. However, because local governments are required announce the day-off on the previous day, day t-1, they can only make decisions based on the weather forecasting on day t-1. I therefore control for rainfall, wind speed, and route on day t-1. The interaction between wind speed and the typhoon route is intended to capture the decision-making process. When the typhoon wind speed exceeds the warning level, but the typhoon route is not close to the city, then the typhoon doesn't impact the city, hence no day-off order is issued.

I also control for confounding factors that may influence the total count of passengers in the metro system. For example, the Taipei Metro Company continued to build new stations after 2009, and more stations attract more passengers. Also, commuters cause the passenger numbers to fluctuate because of weekends or school vacations. To control those confounders, I include national holiday (*nholiday*) and time trends in equation (1), including day of week (*DOW*) and month of the year (*MOY*). Finally, ε_t is the error term of estimation.

People received day-off orders (*doff*) on day t-1, but day-off occurs on day t. In addition, people also make decisions based on the weather conditions of day t. People might not exhibit avoidance behavior when the weather was good on day t. I therefore illustrated this situation with specification (2) as follows. The first bracket shows the past information on day t-1, and the second bracket represents the information on day t.

$$\log(PS_t) = \rho_1 \log(PS_{t-1}) + \rho_2 \log(PS_{t-2}) + \alpha_1 nholidy_t + \alpha_2 DOW + \alpha_3 MOY + [\beta_1 doff_t + \gamma_1 wind_{t-1} \cdot route_{t-1} + \gamma_2 rain_{t-1}] + [\rho_1 rain_t + \rho_2 wind_t] + \varepsilon_t \qquad (2)$$

Because Taipei city and New Taipei City are adjacent, many people travel from New Taipei City to Taipei city to work or go to school. Therefore, as illustrated in specification

(3) I estimate the interaction effect of rainfall from both the Taipei government and the New Taipei government.

$$\log(PS_t) = \rho_1 \log(PS_{t-1}) + \rho_2 \log(PS_{t-2}) + [\beta_1 doff_{Tait} + \gamma_1 wind_{t-1} \times route_{t-1} + \gamma_2 rain_{Tait-1} + \gamma_3 rain_{NTait-1}] + \alpha_1 nholidy_t + \alpha_2 DOW + \alpha_3 MOY + \varepsilon_t \tag{3}$$

$$\log(PS_t) = \rho_1 \log(PS_{t-1}) + \rho_2 \log(PS_{t-2}) + [\beta_1 doff_{Tait} + \gamma_1 wind_{t-1} \times route_{t-1} + \gamma_2 rain_{Tait-1} + \gamma_3 rain_{NTait-1}] + [\rho_1 rain_{Tait} + \rho_2 rain_{NTait} + \rho_3 wind_{Tait} + \rho_4 wind_{NTait}] + \alpha_1 nholidy_t + \alpha_2 DOW + \alpha_3 MOY + \varepsilon_t \tag{4}$$

Next, I examine the general avoidance behavior in Miami-Dade County to alarms (not mandatory orders) through specification (5). $alarm_T$ is the total number of alarms issued by NOAA during period *t*. I examined different lag periods for alarms, including contemporaneous (t) and one and two period lags (t-1 and t-2).

$$\log(PS_t) = \rho_1 \log(PS_{t-1}) + \rho_2 \log(PS_{t-2}) + \beta_1 alarm_T + \gamma_1 wind_t + \gamma_2 rain_t + \alpha_1 DOW + \alpha_2 MOY + \varepsilon_t \tag{5}$$

As briefly discussed in section 3, I use hurricane watches and hurricane warnings for Miami-Dade County to estimate the avoidance behavior when people receive alarms of severe tropical cyclones through specifications 6a, 6b, and 6c. $Hurricane\_watch_{t-2}$ is the hurricane alarm people receive where I use two lag periods because the announcement occurs 48 hours in advance. Similarly, $Hurricane\_warning_{t-1}$ is the hurricane alarm people receive, where I use one lag period because the hurricane warning is announced 36 hours in advance. According to NOAA, people should prepare extra supplies and plan for evacuation when receiving a hurricane watch, and people should be well-prepared or leave when receiving a hurricane warning. If the alarm is the only information people rely on, they will make plans accordingly.

$$\log(PS_t) = \rho_1 \log(PS_{t-1}) + \rho_2 \log(PS_{t-2}) + \beta_1 Hurricane\_Watch_{t-2} + \alpha_1 DOW + \alpha_2 MOY + \varepsilon_t \tag{6a}$$

$$\log(PS_t) = \rho_1 \log(PS_{t-1}) + \rho_2 \log(PS_{t-2}) + \beta_1 Hurricane\_watch_{t-2} + \gamma_1 wind_t + \gamma_2 rain_t + \alpha_1 DOW + \alpha_2 MOY + \varepsilon_t \tag{6b}$$

$$\log(PS_t) = \rho_1 \log(PS_{t-1}) + \rho_2 \log(PS_{t-2}) + \beta_1 Hurricane\_watch_{t-2} + \beta_2 Hurricane\_warning_{t-1} + \gamma_1 wind_t + \gamma_2 rain_t + \alpha_1 DOW + \alpha_2 MOY + \varepsilon_t \tag{6c}$$

V. Results

(1) Avoidance behavior

Table 4 presents the results for how day-off orders affect passenger trips for Taiwan. The first two columns show estimates for Kaohsiung, and the other two columns present estimates for Taipei and New Taipei. All four specifications offer evidence that people exhibit avoidance reactions in response to day-off orders. In specifications (1) and (3), the passenger trips drop 71.20% and 94.78% and are significant at the 1% level, respectively. In specifications (2) and (4), people also respond to day-off orders, and there are 58.08% and 83.87% reductions in passenger trips in Kaohsiung and Taipei, respectively. When the specification includes current period weather information, the impacts of day-off orders become smaller in both cities.

Referring to Figure 1, Kaohsiung city is located in southern Taiwan. Typhoons on Route 7 have a stronger impact than on Routes 4 to Kaohsiung city because when a typhoon makes landfall from Route 4, the magnitude of a typhoon is reduced by the Central Mountain Range. However, if a typhoon makes landfall on Route 7, the power is not reduced by the mountain range and is even stronger because the ocean provides more energy to sustain the typhoon. As shown in Table 4, when the wind speed in period t-1 increases, typhoons on Routes 4 and Route 7 are associated with significant reductions in passenger trips. Moreover, the coefficient on the Route 7 variable is larger than Routes 4. However, in Taipei and New Taipei, typhoons that follow Route 2 have stronger impacts than other routes.

Turning to other non-typhoon results, national holidays generate different patterns across metro systems in the two cities. In Kaohsiung, more people use the metro system, with 15.9% increase in passenger trips on holidays. However, in Taipei and New Taipei, fewer people use the metro system during holiday periods, with around a 20% drop in passenger trips. These different patterns are due to the fact that more people live in Northern cities for work, but they go home to other cities for national holidays.

Table 4. Estimated impacts of day-off order on amount of passengers (fixed-effect)

	Kaohsiung		Taipei & New Taipei	
Specification	**(1)**	**(2)**	**(3)**	**(4)**
ln (PS_{t-1})	0.6242***	0.6168***	0.5134***	0.5259***
ln (PS_{t-2})	0.0942***	0.1049***	0.3241***	0.3082***
$doff_t$	-0.7120***	-0.5808***	-0.9478***	-0.8387***
$rain_{t-1}$	0.0012**	0.0015***	0.0008***	0.0010***
$wind_{t-1} \times route_{t-1}$				
0	-0.0002	-0.0002	0.0009**	0.0013***
1	-0.0000	0.0001	0.0028***	0.0033***
2	0.0023***	0.0017*	0.0102***	0.0102***
3	0.0015*	-0.0018**	0.0057***	0.0059**
4	-0.0012*	-0.0004	0.0014***	0.0015***
5	0.0004	0.0002	0.0006	0.0010
6	-0.0005	-0.0003	0.0006	0.0010
7	-0.0019*	-0.0007	-0.0005	-0.0007
9	0.0009	0.0008	0.0001	-0.0006
10	0.0008	-0.0000	-0.0008	-0.0002
$Kaohsiungrain_t$		-0.0014***		
$Kaohsiungwind_t$		-0.0017		
$Taipeirain_t$				-0.0013***
$Taipeiwind_t$				0.0104***
$NewTaipeirain_t$				-0.0001
$NewTaipeiwind_t$				-0.0232***
Nhday	0.1590***	0.1596***	-0.2071***	-0.2066***
R-squared	0.7407	0.7518	0.7901	0.8029

*:10%, **:5%, ***:1% statistic significant.

Table 5 presents results for avoidance behavior in Miami-Dade County, which shows a 30% reduction in bus rides due to hurricane warnings. For comparison, note that in Tiawan passenger rides are also reduced by around 10% when people receive alarms. One important related finding is that bus rides in Miami-Dade County are sensitive to weather conditions, such as wind and precipitation. For comparison, a 1% increase in precipitation causes a 0.2% decrease in passenger rides in Kaohsiung but a 9% decrease in Miami-Dade County. A possible explanation is that bus stops do not provide cover or transit tunnels between buildings. But the subway system in Kaohsiung is underground, and each railway stop is in a building or close to a building. The difference between the two types of transportation systems may result in different passenger behaviors. However, I also estimated regressions for Metrorail and Metromover, and the results were similar to the bus system. These findings lead to a second possible explanation, which is that residents in Miami-Dade County rely more on weather conditions for daily decisions than do residents of Taiwan.

Table 5. Avoidance behavior _Miami Dade County Metrobus system (fixed-effect)

Specification	(5a)	(5b)	(5c)	(5d)
$\ln(\mathbf{busride}_{t-1})$	0.452***	0.455***	0.472***	0.455***
$\ln(\mathbf{busride}_{t-2})$	-0.024	-0.037	-0.049	-0.047
Awind	-0.006***	-0.007***	-0.008***	-0.007**
Rain	-0.071***	-0.072***	-0.071***	-0.071***
Alarm	-0.302***			
$\mathbf{Alarm}_{t-1}$		-0.269***		-0.182***
$\mathbf{Alarm}_{t-2}$			-0.257***	-0.154***
constant	6.579***	6.723***	6.657***	6.832***
R-squared	0.779	0.777	0.776	0.778

*:10%, **:5%, ***:1% statistic significant.

I use transportation data to proxy people's avoidance behavior, and the results presented in Tables 4 and 5 provide evidence of avoidance behavior. However, I also want to examine the degree to which people engage in avoidance behavior regardless of whether government officials announce a day off or issue a warning. Unfortunately, for Taiwan data limitations prevent such analyses. Therefore, I introduce Miami-Dade County, which has a similar total population, public transportation usage rate, and weather conditions to

Kaohsiung City, and compare transportation usage during hurricanes under a warning-only scenario.

As described in section 3.2, NOAA issues different types of warnings related to the magnitude of tropical cyclones. From Table 1, in the case of Taiwan government officials are more likely to a announce day-off with moderate and severe typhoons. Therefore, I select similar magnitude tropical storms in Miami, which are storms categorized as hurricanes. I test the specification when people receive a hurricane watch and hurricane warnings to identify avoidance behavior when people receive information without mandatory orders. Table 6 shows that in Miami-Dade County transportation usage drops 70.7% and 73.0% two days after people are informed of a hurricane with and without controlling for weather[18], respectively. The avoidance magnitude is similar to Kaohsiung City in the case of a mandatory day-off order.

Table 6. Avoidance behavior _Miami Dade County bus system with different warning types (fixed-effect)

Specification	(6a)	(6b)	(6c)
$\mathbf{ln(busride_{t-1})}$	0.398***	0.386***	0.377***
$\mathbf{ln(busride_{t-2})}$	-0.061**	-0.055*	-0.049*
Awind		-0.006***	-0.005***
Rain		-0.069***	-0.069***
$\mathbf{Hwatch_{t-2}}$	-0.730***	-0.707***	-0.425***
$\mathbf{Hwarning_{t-1}}$			-0.245***
Constant	7.623***	7.727***	7.765***
R-squared	0.789	0.796	0.805

[18] This reduction might be because NOAA issues a hurricane watch 48 hours in advance and recommends people prepare and review personal evacuation plans.

VI. Conclusions

Tropical cyclones cause tremendous damage in regions, and some scientists believe that both the frequency and the intensity of tropical cyclones will increase due to climate change (IPCC, 2012). Since the 1980s, the Taiwanese government has implemented typhoon day-off orders and alarms in an effort to reduce fatalities and the economic impacts of typhoons. The alarms and day-off orders provide information and guidelines upon which the public make avoidance decisions. I used aggregate transportation data from 2009 to 2019, combined with information on fifty typhoons, to evaluate the degree to which avoidance behavior is influenced by typhoon warnings and mandatory day-off policies. The findings show that people respond to typhoon day-off orders in differing magnitudes. In Taipei and Kaohsiung cities, the analysis indicated that there is a 60% to 95% drop in metro passenger trips when day-off orders are announced. If people receive typhoon alarms, there is a 5% to 10% drop in metro passenger trips.

However, day-off orders become controversial and costly when governments announce them in advance based on forecasts, but typhoons change paths such that the order was not needed. Whether a policy mandates action or simply provides adequate warning information, if the magnitude of the avoidance behavior response is similar, it would seem that the two policies are equally effective. However, according to the New Media Lab in Taiwan, between 2006 and 2015, recorded wind speed and rainfall data indicate that the magnitude of tropical cyclones often did not meet the criteria for declaring a day off. In Taichung City, a major manufacturing hub in central Taiwan, the rate of unnecessary day-off declarations was 73%[19]. This suggests that the mandated day-off orders may result in relatively greater economic costs due to weather forecasting error.

This article further examines avoidance behavior during similarly severe tropical cyclones but without mandatory orders. Due to data limitations, comparing avoidance behaviors before and after the adoption of the day-off order policy in Taiwan is not feasible. Additionally, the dataset does not provide comparable intensities of tropical cyclones with and without mandatory orders. Consequently, I selected a comparable case, Miami-Dade County, based on several perspectives, including the data availability, frequency of tropical cyclones, environmental and demographic considerations, and characteristics of public

[19] See: https://udn.com/upf/newmedia/2015_data/20150930_udntyphoon/udntyphoon/index.html

transportation usage. The results indicate a similar level of avoidance behavior in Miami-Dade County, where people respond to hurricane watches by reducing bus passenger trips by about 70%. This study provides valuable insights that contribute to the ongoing discussion surrounding mandatory day-off policies. The evaluation demonstrates that people respond to alarms and instructions aimed at minimizing disaster exposure, with this response being comparable in magnitude to that observed with mandatory orders.

Mandatory orders may be deemed necessary in situations where information is incomplete and there is a high degree of uncertainty. However, in regions where residents possess substantial experience and knowledge of natural disasters, governments may find it sufficient to provide information and empower school authorities and business owners/managers, as well as residents, to make avoidance decisions based on their temporal and spatial circumstances. For instance, there was considerable public outcry following the late announcement by local authorities in Florida, which many believe contributed to the 125 deaths resulting from Hurricane Ian in 2022. However, upon closer examination of victim characteristics, a relatively high portion were new residents who were unfamiliar with hurricane exposure. Even though the government provides information, those who are unaware or have less experience may fail to take appropriate safety measures when a tropical cyclone approaches.

Although utilizing aggregate data represents a novel approach in studying avoidance behavior during natural disasters, due to data limitations this article does not offer a cost-benefit analysis of scenarios with and without mandatory orders. Also, I do not have information about individual perspectives, such as trust or past disaster exposure experiences. Exploring alternative data sources, such as smartphone tracking data, holds promise for future research. More granular data may unveil precise timing and locations, enabling the calculation of social costs and offer enhanced recommendations to policymakers.

CHAPTER 2: Efficacy analysis of cloud seeding program in Kansas agriculture

I. Introduction

Hailstorms cause tremendous economic losses in the United States (US) and across the globe. From 2003 to 2023, severe hailstorms caused $35.8 billion in losses in the US (NOAA, 2024)[20]. Moreover, hailstone size may increase in the central US and could potentially cause more damage in the future, according to meteorology simulations (Fan et al., 2022).

To mitigate hail damage, more than 50 countries around the globe have adopted weather modification programs, more specifically, cloud seeding, for hail suppression purposes since the 1970s, including the US, Russia, France, Spain, Romania, Argentina, etc.[21] The microphysical process of hail formation is extensively discussed in the literature (Lamb and Verlinde, 2011; Allen et al., 2020; see section II for more details). The main idea of cloud seeding for hail risk reduction is to launch chemical particles into clouds, thereby reducing the frequency and magnitude of hailstones (Knight, 1977).

Most existing research on the effectiveness of cloud seeding programs evaluates factors such as the size and volume of hailstones, the frequency of hail events, and the distribution of hailstone sizes over a certain period (Bergant, 2011; Changnon, 1971; Dessens et al., 2016; Gavrilov et al., 2013; Rivera et al., 2020; Spiridonov et al., 2015). Among these studies, the intensity of hail is often measured by the size of the hailstones, as smaller hailstones, which have less kinetic energy, are associated with less damage to crops, livestock, property, and even humans (Pirani et al., 2023; Púčik et al., 2019).

However, the relationship between the size of hailstones, frequency of hail events, and crop damage is not yet clear. In the literature, there are relatively few studies that examine the effect of cloud seeding hail suppression in reducing crop loss, but more studies on direct property damage (Allen et al., 2020; Changnon & Changnon, 2000; Childs et al., 2020). Childes et al. (2020) conducted interviews with farmers, revealing that most farmers

[20]This number represents the costs attributed solely to hailstorms, although instances of tornado outbreaks, high winds, and hailstorms often occur concurrently. Furthermore, disaster costs in NOAA reports encompass damages to residential and commercial properties (including buildings, vehicles, and boats), infrastructure (such as roads, bridges, and electrical facilities), agricultural assets (including crops, livestock, and timber), as well as losses related to business interruptions.

[21] See World Meteorological Organization: https://public-old.wmo.int/en/resources/bulletin/seeding-change-weather-modification-globally

worried about small-size large-volume hailstones more than large-size hailstones. Also, Púčik et al. (2019) indicate hailstones size of 2 to 3 centimeters (around 1 inch) in diameter damage crops most. Therefore, measuring hailstone size and the frequency of hail events might not be an appropriate approach for evaluating hail suppression program effectiveness. In other words, cloud seeding might reduce the frequency and magnitude of hailstones but could potentially cause more damage. The effectiveness of cloud seeding on crop loss remains ambiguous[22].

Only a few studies examine the effectiveness of hail suppression programs on crop damage and productivity. Soviet scientists provided hail suppression by launching rockets into clouds, reporting a 50% to 90% reduction in crop hail damage (Federer et al., 1986). Abshaev et al. (2023) indicated that over the past 65 years, Russia improved its rocket seeding technology, thereby reducing hail crop damage by as much as 86%. In the US, Knowles and Skidmore (2021) found that cloud seeding in North Dakota resulted in a 13% increase in wheat yields per harvested acre and a 0.548 decrease in the wheat loss ratio in North Dakota. According to research by Ekland et al. (1999), cloud seeding reduced the crop loss ratio by 27% in Kansas and minimized damaged planted areas by 34% to 48%.

One concern regarding cloud seeding for hail suppression is the potential reduction in rainfall in downwind areas. When a downwind region receives less precipitation or more hailstones after cloud seeding in the target areas, it is referred to as the downwind effect. This effect has been a concern for northwest Kansas counties that terminated cloud seeding programs. However, while the downwind effect has been discussed in the context of cloud seeding for rain enhancement purposes, it has not received much attention in the hail suppression context (Solak et al., 2003; DeFelice et al., 2014; Wang et al., 2019). Only a few studies have explored the potential rainfall changes in hail suppression areas. For example, the Kansas Water Office, responsible for cloud seeding operations in Kansas, reported a decrease of 0.25 inches in average precipitation during the growing season in the targeted areas (Eklund et al., 1999). Conversely, in Alberta, there was a 2.2% increase in rainfall in hail suppression areas (Krauss and Santos, 2004).

[22] The relationship between hail magnitude and damage also depends on growth stage of crop, canopy position of crops, weather, and water management (Holman et al., 2022). For example, cotton is more vulnerable to hail in the bud stage than in the boll stage (McGinty et al., 2019; Yue et al., 2019).

When policymakers decide whether to continue a policy, providing an evaluation of its efficacy is crucial. In the literature, the most common measurements are the size of hailstones and the frequency of hail events. In this study, I use a broader set of measurements to evaluate the efficacy of the cloud seeding program, including its impact on hailstone size and frequency, crop damage, and crop yields, while also considering potential downwind effects. The purpose is to evaluate the degree to which choosing different measurements may lead to different conclusions. When different measurements yield conflicting conclusions, it can spark discussions and encourage collaboration to improve the technology or management of the program.

Kansas serves as a fitting focal point for this analysis due to its status as a prominent producer of winter wheat, corn, and sorghum in the US, and the significant hail damage experienced by its crops. I use county level data over the 2002-2020 period for Kansas in this paper. As a prelude to the full set of findings, the analysis shows that cloud seeding is associated with reductions in hail size in target areas. Even though the size of hailstones decreases, there are no statistically significant reductions in hail or drought damage. However, the results indicate that cloud seeding is associated with more flooding damage to crops. This finding is consistent with the literature that severe rain or inundation can occur in target areas after cloud seeding (Almheiri et al.,2021; Spiridonov et al., 2015; Tuftedal et al., 2022; Yoo et al., 2022). Lastly, the findings indicate that cloud seeding enhances corn productivity within the seeding area but diminishes sorghum productivity in downwind areas. Leveraging these outcomes, I conduct a cost-benefit analysis of the Kansas cloud seeding program. While the overall net present value of the program is positive, it is essential to recognize that this is not universally beneficial; certain counties, particularly those downwind, exhibit negative net present values.

The remaining sections of this chapter are structured as follows: Section II provides an introduction to cloud seeding in Kansas. The methodology and data are outlined in Sections III and IV, respectively, followed by the presentation of results in Section V. Section VI presents the cost-benefit analysis. Finally, conclusions and policy implications are discussed in Section VII.

II. Background

This section begins with a discussion of the primary rationale behind considering cloud seeding as a promising method of reducing hail. I also provide an overview of research findings related to cloud seeding efficacy. The section concludes with a detailed discussion of the Kansas cloud seeding project.

(1) Cloud seeding for hail suppression

The hail formation process is well-documented in the literature (Allen, 2020). Two primary components are essential for hailstone production: supercooled water and embryos. Supercooled water refers to liquid water persisting below the freezing point of pure water for an extended duration. This phenomenon often occurs in convective cloud systems where updrafts bring cloud condensation nuclei (CCN) into the cloud. Condensation of water vapor on these CCNs results in the formation of supercooled water droplets.

The merging of supercooled water droplets, typically due to contact with embryos, initiates a chain reaction of freezing processes, leading to the formation of hailstones. Small hailstones may revert to embryos, attracting more supercooled water, sustaining the freezing process, and allowing for further growth. Hailstones eventually fall when they reach a size too substantial to be supported within the clouds.

According to microphysical theory, the core concept behind cloud seeding is to stimulate beneficial competitiveness processes. This theory posits that natural embryos in clouds, such as dust or pollen, may not be plentiful enough. Consequently, the introduction of artificial embryos, like silver iodide or dry ice, can compete with natural embryos, preventing the overharvesting of supercooled water droplets by natural embryos. The expected result is that all hailstones should be smaller than those without seeding. Smaller hailstones have the potential to melt before reaching the ground, effectively mitigating potential hail damage.

The promise of controlling hail damage through cloud seeding led to extensive investigations dating back to the 1970s. During this period, several multi-year projects aimed to explore the beneficial competitiveness hypothesis and assess the feasibility of cloud seeding technology.

From 1972 to 1976, the National Hail Research Experiment (NHRE) spanned multiple states in the US, including Northeast Colorado, Kansas, Nebraska, and Wyoming. However, the results revealed no statistically significant effects in reducing the frequency and size of hail (Allen et al., 2020; Foote et al., 1979; Knight and Squires, 1982; Squires and Knight, 1982). Subsequent to NHRE, from 1977 to 1982 Switzerland, Italy, and France initiated the Grossversuch IV project to test Soviet hail suppression technology. Similar to the NHRE, the results demonstrated no statistically significant difference in hail frequency and magnitude between seeded and non-seeded areas (Federer et al., 1986). A reexamination of the Grossversuch IV project data by Auf der Maur and Germann (2021) even suggested that cloud seeding might increase the kinetic energy of hailfall, potentially intensifying damages.

Despite inconclusive results from experimental projects, countries worldwide persisted in their investment in cloud seeding for hail suppression. Real-world seeding data played a pivotal role in evaluating the efficacy of these programs. In Slovenia, Serbia, and Argentina, no statistically significant changes were observed in either the frequency or magnitude of hailstorms (Bergant, 2011; Gavrilov et al., 2013; Rivera et al., 2020). Greece and Spain witnessed a reduction in hailstone magnitude without a significant impact on frequency (Spiridonov et al., 2015; Dessens et al., 2016). In contrast, A study in France indicated that cloud seeding resulted in a substantial decrease in both the frequency and magnitude of hailstones (Changnon, 1971). These diverse outcomes highlight the complexity and variability in the effectiveness of cloud seeding initiatives across different geographical regions.

(2) Weather modification in Kansas: A four-decade cloud seeding initiative

Cloud seeding has been a cornerstone of weather modification efforts in the US for six decades. Among the states actively adopting cloud seeding, Kansas, along with North Dakota and Texas, stand out, implementing this technique primarily during the warm season[23]. The focus in these states has been on hail suppression and rain enhancement, with occasional applications for fog dispersion.

[23] Several states in the US have implemented cloud seeding during different seasons and for various purposes. States such as California, Nevada, Idaho, Utah, Wyoming, and Colorado employ cloud seeding in the cold season for snowpack augmentation and rain enhancement, with primary objectives aimed at increasing water storage in reservoirs and replenishing groundwater. While cloud seeding has been proven to increase rainfall and runoff by an average of 10% to 20% (Rosenfeld and Woodley, 1989; Bruintjes, 1999; Flossmann et al., 2019), its efficacy for hail suppression remains a subject of controversy.

To emphasize the risk and exposure to hail, Figure 6 illustrates the distribution of severe hail—defined as hailstones over 1 inch (25.4 mm) in diameter—across the US[24]. The map depicts the significant threat posed by hazardous hail events, particularly in the Great Plains region, including Kansas. In 2022 alone, Kansas experienced 289 major hail events, ranking it fourth among states in hailstone frequency after Texas, Nebraska, and Minnesota. This highlights the pressing demand for effective measures to abate the costly impact of severe hailstorms[25].

Among the states, Kansas leads in winter wheat and sorghum production in the US and ranks among the top ten states for corn production. Agriculture contributes $81 billion to Kansas's economy, with approximately 88% of the state's land dedicated to farmland for crops and livestock. According to the Kansas Crop Planting Guide[26], winter wheat should be planted from mid-September to late October, varying depending on geographic zones, with harvest taking place the following summer. Corn and sorghum are typically seeded between late April and mid-May. However, vulnerability to hailstorms, prevalent from April to September, poses a threat to the pre-mature stages of wheat and silk corn, leading to potential crop yield losses. The rapid onset of damage within minutes makes cloud seeding programs desirable in Kansas to mitigate forecasted crop-damaging hail.

The Kansas Water Authority is the key entity managing the cloud seeding program in Kansas[27]. In the 1990s, the western part of Kansas was the primary target for cloud seeding. However, a five-year program faced suspension due to protests led by the grassroots group, Citizens for Natural Weather[28]. Their opposition was not rooted in doubts about hail suppression efficacy but in concerns that seeding clouds might alter local and adjacent precipitation patterns. In 1999, four northern Kansas counties voted to withdraw from the cloud seeding program. The present study focuses on the southwestern part of Kansas, where 14 counties agreed to participate in the cloud seeding program in 2002 as shown in Figure 7 (blue area).

---

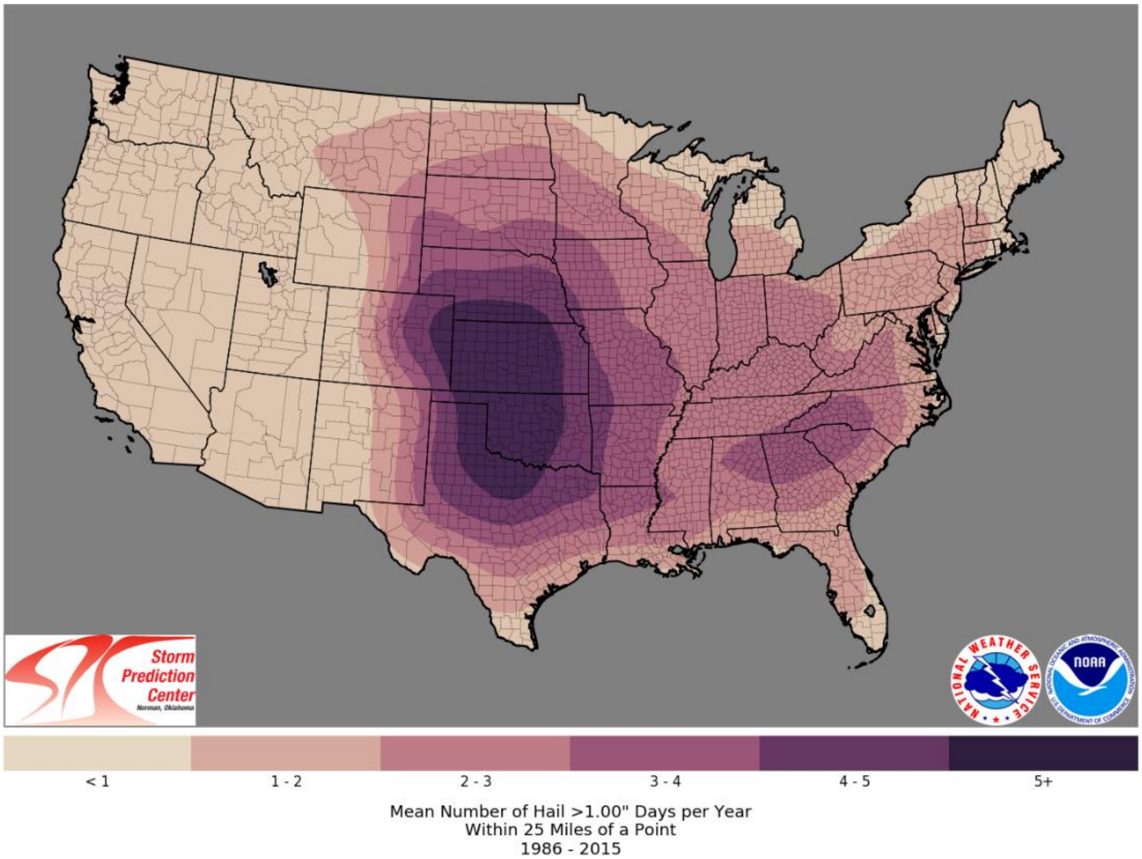
[24] The National Centers for Environmental Information (NCEI) identifies severe hail based on the diameter of hailstones. Appreciable damage occurs only when the diameter is over 1 inch (25.4 mm). The threshold for damaging hail size was adjusted in 2010 from 19.1 mm to 25.4 mm, as suggested by stakeholders (NCEI, 2009). It's worth mentioning that larger hailstones tend to be less spherical (Allen, 2020).

[25] See: https://www.iii.org/table-archive/22795.

[26] See: https://bookstore.ksre.ksu.edu/pubs/l818.pdf.

[27] Kansas Water Authority is within and as part of the Kansas Water Office.

[28] See: https://www.latimes.com/archives/la-xpm-2000-jun-11-mn-39711-story.html



Source: NOAA

Figure 6. Hail distribution in Great Plains

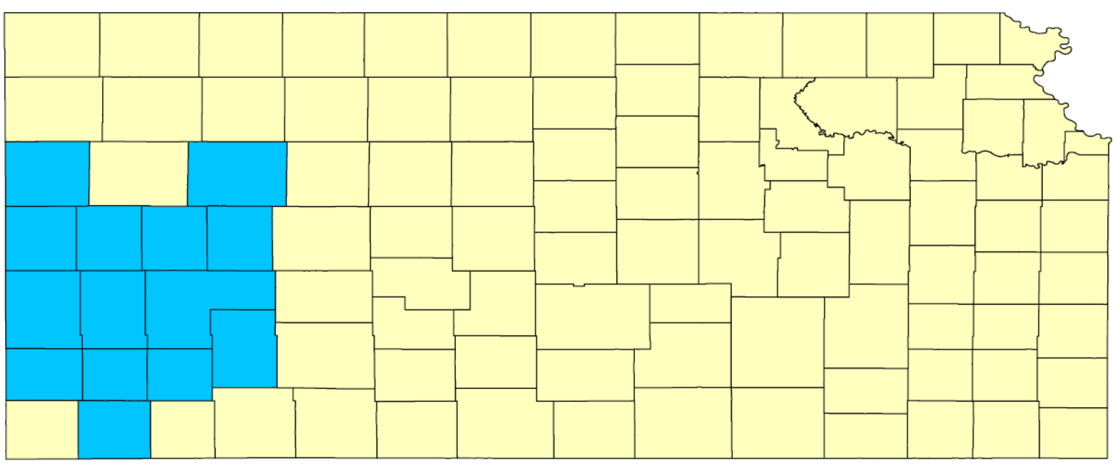
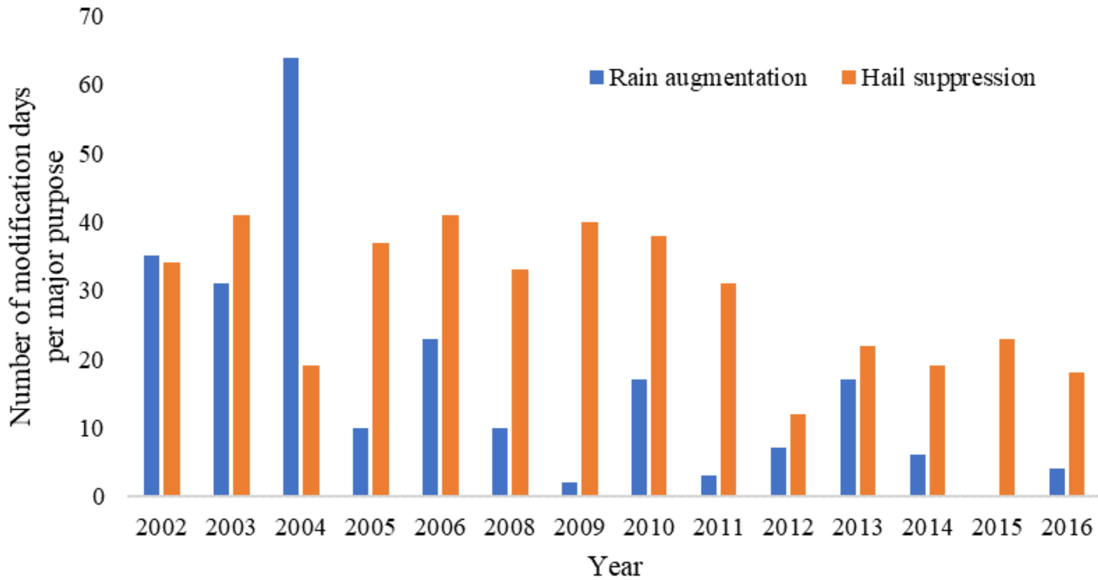


Figure 7. Map of counties participating in the cloud seeding project (2002, Kansas)

The Kansas Water Office executed an Operational Plan for the Weather Modification Project, where the project manager made daily seeding decisions based on the Operation Plan and meteorological data during the program's active period[29], typically from April to September. On a daily basis, the project manager assesses all available data to determine the seedability of incoming clouds. If a seeding decision is made, the project manager contacts the pilot and crew to confirm the seeding strategy. Following mission completion, pilots report cloud responses and data to the operation center for analysis. The Operation Plan acknowledges the potential spillover effect in adjacent areas, impacting not only the downwind but also the upwind areas, with buffer zones set at 25 and 10 miles, respectively.

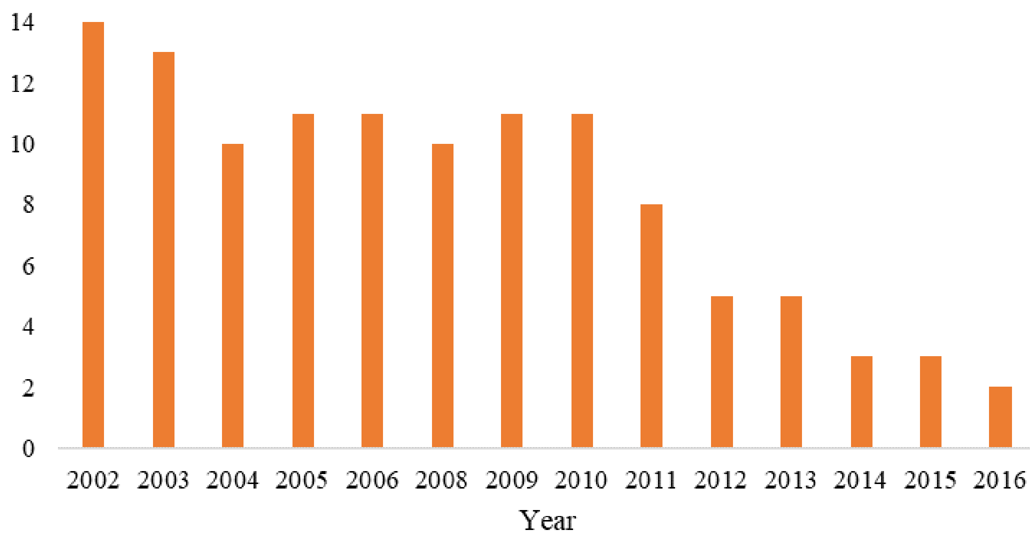
Cloud seeding programs in Kansas have dual objectives, focusing on both hail suppression and rain augmentation. According to the Operation Plan, hail suppression generally takes precedence over rain augmentation. However, adjustments are made based on soil moisture levels and crop growth stages, with priority given to areas vulnerable to hail risks. Additionally, when a convective cloud system is unstable, the seeding mission shifts from rain augmentation to hail suppression. Operation records align with the Operation Plan, revealing that from 2002 to 2020, cloud seeding days were 65% for hail suppression and 35% for rain augmentation, as illustrated in Figure 8. Nevertheless, the number of counties participating in the cloud seeding project has declined over time, with no Kansas counties in the program since 2017 (see Figure 9). As of 2022, Kansas is no longer affiliated with the North American Weather Modification Council.

[29] Meteorological data comprise hourly observations, aviation terminal forecasts, severe weather warnings, synoptic surface and upper air analyses, storm data within the operational area, and satellite imagery.



Data source: NOAA.

Figure 8. Number of modification days for hail suppression and rain enhancement in Kansas



Data source: NOAA.

Note: In total, there are 105 counties in Kansas. 2007 data is missing.

Figure 9. Numbers of counties participating in Kansas cloud seeding program

III. Methodology

(1) Model

The cloud seeding program is a jointly funded initiative by county governments and the Kansas state government. Each year, the state government invests around $240,000 to support the radar system, which is the most expensive component of the program. County governments decide annually whether to participate in the program and determine their contributions based primarily on population.

To model the decision-making process, I adapted the framework developed by Brien and Eger III (2021), which explores a jointly funded program between state and sub-state governments. In this model, different levels of government compete to reduce their contributions while still maintaining the provision of the public good. Brien and Eger III's (2021) model builds on the work of Hettich and Winer (1984, 1988), who developed a normative model of tax structure to identify the motivations behind government decisions. Their model assumes that the aim of government officials is to maximize voter support, rather than acting as altruistic or omnipotent social planners. In this model, there are M county governments and one state government. County level elected officials seek to maximize utility specifically related to the jointly funded program. For a representative county j, there are N people living in the county.

County government official maximization problem:

$$Max\ U_j = \sum_{i=1}^{N} b_i\left(\alpha_j \cdot \bar{E}_j\right) - s\left(\alpha^u \bar{E}_j^u\right) - c_i(v_i)$$

$$\text{Subject to } \bar{E}_j = L_j + \bar{A}$$

$$\text{where } v_i = \frac{L_j}{N}$$

The local government elected official decides whether to participate in the program, with α as a binary variable (1 for participation, 0 otherwise). Once the county official decides to participate, he/she then determines the annual expenditure, $\bar{E}$, on the cloud seeding program. When the county adopts the program, it generates benefit for the residents. The political support to the county official can be expressed as $b_i(\alpha \cdot \bar{E})$, representing voter i's expected support for the county official due to the expenditure on cloud seeding program

(Hettich and Winer, 1988). For example, spending on cloud seeding might reduce hail damage to farmer i's crops in the county, leading farmer i to support the county government official and thus increase the likelihood of success in the next election. While the expenditures ($\bar{E}$) could in principle depend on other variables, for simplicity $\bar{E}$ is constant.

The political cost refers to the cost of levying taxes from taxpayers, represented by the function $c_i(v_i)$. In the function, v_i may represents not only the taxes paid by voter i, but also the broader deadweight loss associated with taxation (Hettich and Winer, 1988). The specific definition of v_i depends on the design of tax collection and the goals of the research. Within the framework envisioned by Hettich and Winer (1988), all farmer production functions and taxable activities are included in the model, whereas Brien and Eger III's (2021) assume identical taxpayers, with each paying the same amount of tax for the project, represented as $v_i = \frac{L}{N}$. I follow Brien and Eger III's (2021) in this research because the focus is on the efficacy of cloud seeding program where local government contributions to covering the cost of cloud seeding are based on population size[30].

Expenditure on cloud seeding program is equal to the county government's contribution, denoted as L_j, plus, the contribution from the state government, denoted as $\bar{A}$.

One key difference in my model and that of Brien and Eger III's (2021) and Hettich and Winer (1988) is the function of $b_i()$. They assumed that $\partial b_i / \partial \bar{E} > 0$, which indicates that expenditure on the jointly funded program effectively corrects externalities. Although cloud seeding is intended to suppress hail damage, its effect might be zero or even negative. A key goal of this chapter is to test the effectiveness of cloud seeding program. If the program results in a negative or zero impact on farmers in the county and leads to reduced political support, the outcome to the maximization problem would be to terminate the program, where $\alpha = 0$.

For a cloud seeding program, the political support in the county might be influenced by decisions made by upwind counties, i.e., a spatial spillover effect, represented by $s\left(\alpha^u \bar{E}_j^u\right)$. As mentioned in background section, one potential and controversial spillover effect of cloud seeding program is a reduction in rainfall in downwind areas. For example,

[30] According to the *Council Grove Republican*, "County governments normally pay between $12,000 and $35,000 each year to help finance the weather effort, depending on population" (May 7, 1996, p. 2).

farmer i might experience reduced rainfall and adverse impacts on flood and crop production, which could consequently lower the overall probability of voting for the current government. Here, I have not accounted for farmers' risk perceptions, but rather assume that farmers accurately attribute the rainfall reduction to the cloud seeding program rather than other potential causes, such as long-term climate trends.

The state government decides how much contribute to the cloud seeding program but does not control how the funds are distributed among the counties. This is represented as $A_j = \frac{A}{\sum_{j=1}^{M} \alpha_j}$. Therefore, the fewer counties that participate in the program, the more funding each participating county receives. However, reduced county participation may affect the total contribution from the state, which in turn could influence both the efficacy of the cloud seeding program and the potential support for it. For example, Kansas weather modification program officials have noted that too many storms with too few aircraft for cloud seeding missions can negatively impact the program's effectiveness.

Additionally, the state government may be unwilling to contribute to the program if the total contributions from local governments fall below a minimum service threshold, T. If the combined expenditure of all participating counties is less than T, the state government will contribute nothing, resulting in the termination of the jointly funded program. County officials focus solely on their own maximization problem and are unaware of the threshold set by the state government. The state government does not experience spillover effects. If the total political support resulting from funding the cloud seeding program is positive, the state government will pursue the political benefits, even if negative support exists from county j. For the empirical examination, I use data to estimate the political benefit in the form of crop production impacts including spillover effects from the cloud seeding program. In the final section of Chapter II, I presented a cost-benefit analysis using estimated parameters and costs.

(2) Empirical strategy

Based on the model introduced above, three major hypotheses are tested in this study:

Hypothesis 1: Based on the concept of beneficial competition (Detwiler, 2002), participation in a cloud seeding program reduces the frequency and intensity of hailstorms in the target area.

Hypothesis 2: Participation in a cloud seeding program reduces hail damage to crops in target areas.

Hypothesis 3: A spillover effect exists in cloud seeding programs for hail suppression and rain enhancement in downwind areas.

The main idea of cloud seeding program as a damage control agent is based on the concept of beneficial competition (Detwiler, 2002). It assumes that hailstorm frequency and magnitude are functions of cloud seeding, where artificial embryos are introduced into the clouds to compete with natural embryos in supercooled water. The result is an increased production of smaller hailstones that hopefully melt before hitting the ground. Additionally, I test for the presence of and determine whether spillovers are positive or negative. Consequently, cloud seeding potentially reduces crop damage.

To achieve this goal, panel data and the specification presented in equation (1) are employed. In equation (1), m_i controls the characteristics of county *i* that do not vary over a short period, such as altitude, referred to as county-fixed effects. Additionally, λ_t represents time fixed effects, which is included in the model to account for unobserved, time-specific factors—such as El Niño—that could influence the dependent variable across all counties. . Controlling for county and time effects helps to insure the comparability of all observations.

$$Y_{it} = \alpha \cdot seeding_{it} + \beta \cdot UWseeding_{jt} + \gamma \cdot \mathrm{X}_{it} + m_i + \lambda_t + \mu_{it} \qquad (1)$$

Y_{it} represents a set of outcome variables in county *i* in year *t.* I examined several outcome variables that include hail frequency, hail magnitude, crop damage, and crop production. The variable $seeding_{it}$ denotes the cloud seeding program participation in county *i* in year *t*, where 1 indicates participating in cloud seeding program, and 0 otherwise. The parameter α captures the marginal effect of the cloud seeding program participation on outcome variables. Additionally, $UWseeding_{it}$ denotes the seeding decision in upwind county *j* of county *i* in year *t*, with 1 indicating seeding and 0 otherwise. The parameter β captures the spillover effect on outcome variables from the upwind seeding county on downwind county. The vector X_{it} includes covariates such as moisture and temperature, will be discussed further in the Data section below. Finally, μ_{it} denotes the error term.

IV. Data

For testing the hypotheses presented above, data from various sources are compiled:

(1) Cloud seeding data

The cloud seeding data used in this study are derived from the National Oceanic and Atmospheric Administration (NOAA). In compliance with Federal Law[31], all weather modification activities are mandated to submit weather modification project reports to NOAA. For the Kansas cloud seeding program, based on cloud conditions the program operator will call the pilots to standby for data collection or seeding missions. Once the pilots seed the clouds, it will be recorded in the NOAA report. Even if a hailstorm travels into a non-participating county, the program operator cannot require the pilot to execute a seeding mission beyond the boundary of the participating county. Therefore, cloud seeding activities only occur within the boundaries of participating counties. The dataset spans from 2002 to the present and includes information on the counties participating in cloud seeding program.

(2) Hailstorm and weather data

Hailstorm data is obtained from the Next Generation Weather Radar (NECRAD). This dataset provides comprehensive information about the location and magnitude of each hailstorm. The frequency of hail is determined by the total number of hailstorms that occurred during the growing season. The dataset spans from 1955 to 2022 and is aggregated at the county level during the growing season.

Other weather-related data are extracted from the NOAA Climate Data Online (CDO) dataset, which comprises weather observations from various stations. Data for each county are aggregated from various stations within the county. The dataset includes information such as maximum and minimum temperatures. From these data, I computed Growing Degree Days (GDD) and Stress Degree Days (SDD) during the growing seasons, from April to September, using the following formula:

$$GDD = \max\left(0, \frac{T_{max} + T_{min}}{2} - T_{base}\right)$$

[31] Public Law 92-205, or "Weather Modification Reporting Act of 1972".

For GDD, the equation considers the daily mean temperature, calculated as the average of the daily maximum temperatures, T_{max}, and minimum temperatures, T_{min}. T_{base} represents the base temperature for crop growth, which varies by crop type. Specifically, it is set at 40 degrees Fahrenheit for winter wheat (McMaster and Smika, 1988) and 50 degrees Fahrenheit for corn (Cross and Zuber, 1972). If the mean temperature falls below base temperature, GDD is set to zero. The GDD accumulates throughout the growing season. Based on the empirical strategy, I calculated three distinct GDD values for winter wheat, sorghum, and corn. When estimating the impact on crop productivity, I used crop-specific GDD for each crop. For analyzing the impact on crop damage, I chose a base temperature of 40 degrees Fahrenheit, given that winter wheat is the predominant crop in Kansas. This explanation is also included in the section describing the GDD calculation.

For SDD, the formula involves subtracting the upper temperature threshold $T_{threshold}$ from the daily maximum temperature T_{max}. If T_{max} is below $T_{threshold}$, SDD is set to zero. The upper temperature threshold is consistent at 86 degrees Fahrenheit for all crops (Cross and Zuber, 1972). When temperatures exceed 86 degrees Fahrenheit, crops may either cease growth or incur damage.

$$SDD = max\,(0, T_{max} - T_{threshold})$$

On a different note, crop growth relies on adequate moisture. The Palmer Z index, a measure of moisture deviation from normal climate on a monthly basis, is employed. This index, obtained from NOAA[32], distinguishes between wet and dry conditions. Following Knowles and Skidmore (2021), the variables for dryness Dry_{it} and wetness Wet_{it} are calculated as:

$$Dry_{it} = -\min\,(0, PZ_{it})$$

$$Wet_{it} = max\,(0, PZ_{it})$$

A higher count of Dry_{it}/Wet_{it}, indicating a greater deviation from the normal climate, indicates drier/wetter conditions in the county during the growing season. According to NOAA, if Dry_{it} falls between 0 and 1.24, it indicates a normal climate, while a value above 2.75 indicates extreme drought. Similarly, if Wet_{it} falls between 0 and 0.99, it indicates a

[32] See https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/.

normal climate, and a value above 3.50 indicates extreme wetness. From Table 1, on average, the moisture in Kansas during growing seasons is near normal.

(3) Crop data

Crop indemnity data is obtained from the USDA Risk Management Agency Cause of Loss Historical Data Files. These data provide information on indemnity payments and loss ratios for different perils, including hail, drought, and excess moisture (i.e. flood)[33]. The crop loss ratio is defined as the total indemnity divided by the total premium. The total premium comprises the premium paid by farmers plus public subsidy. The target crop loss ratio for US crop insurance is 0.88, indicating that the insurance company retains 12% of the premium to cover unexpected shocks. If the loss ratio exceeds 1, the insurance company is in an unsustainable situation. Additionally, crop yield data for winter wheat, corn, and sorghum, the top three major crops in Kansas, are included in the analysis. The crop yield data are measured in bushels per acre and are sourced from the USDA[34].

(4) Wind direction data

The wind direction data is obtained from the National Aeronautics and Space Administration Land Data Assimilation System 2 (NLDAS-2) dataset, with a resolution of 0.25 degrees[35]. Using QGIS version 3.32.3, wind speed and directions were calculated based on zonal velocity (U wind) and meridional velocity (V wind)[36]. In Kansas, the prevailing wind during the growing seasons (April to September) generally comes from the west, as depicted in Figure 10. This wind direction data is crucial for identifying downwind areas.

[33] In Kansas, 35.8% of indemnity is due to drought, 17.5% due to flood, and 8.2% due to hail.
[34] See USDA National Agricultural Statistics Service: https://quickstats.nass.usda.gov/
[35] 1 degree is equal to 69 miles.
[36] The wind data from NASA is 10 meters above the surface. Although NOAA provided wind data under 17 levels, the resolution of data is 2.5-degree latitude x 2.5-degree longitude global grid.

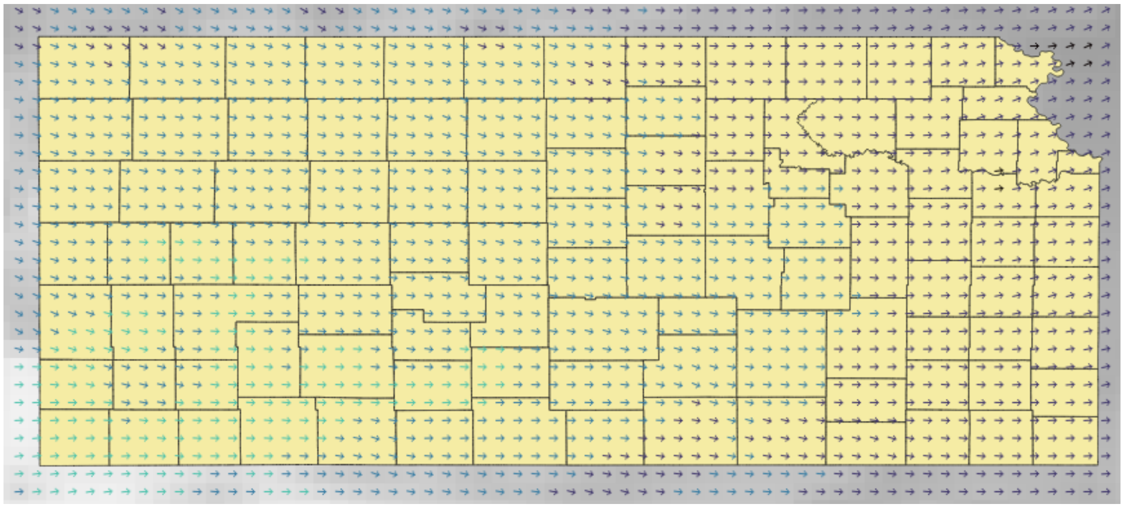


Figure 10. Wind direction in Kansas (2003 July)[37]

Table 7 presents a summary of descriptive statistics. The data gathered from various sources form an unbalanced panel, so the observation numbers differ for each variable. The maximum recorded hail frequency is 94, indicating that 94 hailstorms were observed in one county during the growing season (April to September), with an average of 10.32 hailstorm occurrences during the growing season. Furthermore, the magnitude of hailstorms is evaluated based on the diameter of hailstones. On average, the diameter of hailstones is 1.13 inches, which exceeds the threshold that causes damage to crop plants. The largest hailstone recorded during the period of analysis in Kansas is 3 inches. Additionally, note that the loss ratios for different perils are above 0.88, the design ratio of the USDA. This suggests that the indemnity caused by extreme weather events might be underestimated, and the premium may not be sufficient to cover the indemnity. Table 8 summarizes the definitions and data sources of the variables used in this study.

[37] The Kansas shapefile is from USGS National Boundary Dataset: https://www.sciencebase.gov/catalog/item/59fa9f5de4b0531197affb31

Table 7. Descriptive Statistics for Kansas Sample (County-Level Data, 2002–2020)

Variable*	Obs**	Mean	Std. dev.	Min	Max
Weather					
hail frequency (times/year)	1,890	10.32	8.78	0	94
hail magnitude (inch)	1,890	1.13	0.33	0	3
rainfall (inch)	1,881	3.55	1.30	0.69	9.10
Loss Ratio					
Hail	1,540	2.90	1.69	0.02	17.71
flood (excess moisture)	1,817	1.70	0.99	0.22	8.82
Drought	1,841	2.37	1.10	0	9.78
Yield (bushel per acre					
Sorghum	1,418	67.32	22.92	13	134
winter wheat	1,855	40.82	10.12	12.1	80
Corn	1,654	118.72	38.24	18	225
Production (1,000 bushel)* **					
Sorghum	1,418	2,090	1,908	9.4	12,400
winter wheat	1,855	3,308	2,764	9.0	18,500
Corn	1,654	4,961	5,042	14.8	32,400
Environmental					
GDD40	1,842	3923	835	0	5150
GDD45	1,842	3344	725	0	4535
GDD50	1,842	2770	617	0	3922
SDD86	1,842	487	242	0	1532
Dry	1,890	0.43	0.70	0	3.52
Wet	1,890	0.60	0.79	0	4.46

* Data pertain to the entire year and are not restricted to the cloud seeding season.
**The sample is unbalanced, with varying numbers of years included for each county.
*** This represents the total annual production for each county in Kansas, measured in thousands of bushels.

Table 8. Variable definitions

Variable	Definition	Data Source
Hail frequency	Total number of hailstorms occurs in growing season in county *i*	Next Generation Weather Radar
Hail magnitude	Average diameter of hailstones in growing season in county *i* (inches)	Next Generation Weather Radar
Rainfall	Average rainfall in growing season in county *i* (inches)	NOAA Climate Data Online
Seeding	Participation in a cloud seeding program by county *i* (0 and 1)	NOAA
UWseeding	Participation in a cloud seeding program by upwind county of county *i* (0 and 1)	NOAA and NLDAS-2
Dry	Drought severity deviates from normal weather conditions and is calculated using the Palmer-Z index.	NOAA
Wet	Wetness severity deviates from normal weather conditions and is calculated using the Palmer-Z index.	NOAA
GDD	Growing degree day is a measure of heat accumulation in the growing season, calculated by summing the difference between the daily temperature and the base temperature*.	NOAA Climate Data Online
SDD	Stress degree day is a measure of heat stress on crop plants in the growing season, calculated by summing the difference between the maximum daily temperature and 86 degrees Fahrenheit.	NOAA Climate Data Online
Loss ratio	Total indemnity divided by total premium for each peril	USDA Risk Management Agency
Crop Yield	Crop production bushel per acre	USAD National Agricultural Statistics Service
Crop Production	Total production of crops (winter wheat, corn, and sorghum) in 1,000 bushel	USAD National Agricultural Statistics Service

* The base temperatures are 40 degrees Fahrenheit for winter wheat, 45 degrees Fahrenheit for sorghum, and 50 degrees Fahrenheit for corn.

V. Results and discussion

In this section, I first present the core results obtained from using all Kansas counties. However, to explore the robustness of the findings, I establish a subsample by incorporating nearby counties in adjacent states into the evaluation. Using this broader set of counties, I compute the propensity score for each county. Utilizing these propensity scores, I match counties that adopted and did not adopt the cloud seeding program based on propensity scores and present the estimation results accordingly. Finally, leveraging the parameters derived from the estimation, I conduct an analysis of the costs and benefits associated with the cloud seeding program in Kansas.

(1) Estimating the cloud seeding program impacts in Kansas

Table 9 presents the regression results and estimated effects of the cloud seeding program on hail frequency and magnitude for all Kansas counties. The average size of hailstones in Kansas is 1.13 inches, exceeding the size threshold that might potentially cause damage to crops. The results indicate that cloud seeding programs show no statistically significant effect on hailstorm frequency in target counties or downwind counties. However, estimates indicate that hail size diminishes by 0.10 inches in target areas, which is about 8%, but there is again no statistically significant effect on hail size in downwind areas. Additionally, insufficient moisture in the air as measured by the Dry index correlates with decreased hail frequency and magnitude. Moreover, there is an increase in rainfall of about 0.26 inches in targeted regions, representing approximately 7.3%, with a corresponding decrease of 0.08 inches in downwind areas, although this decrease is statistically insignificant. These results suggest that cloud seeding has not resulted in the "rain steal" phenomenon in this region.

Also, of interest is whether there is evidence that cloud seeding reduces crop damage. In Table 9, the regressions results examining the impact of the cloud seeding program on the crop loss ratio in Kansas are presented. The table reveals that the cloud seeding program had no statistically significant impact on the crop hail loss ratio or the crop drought loss ratio. However, the analysis revealed that the cloud seeding program is associated with an increase in crop flooding damage. Flooding damage, indicative of excessive precipitation, can impede farmers' ability to sow crops or lead to crop damage. As detailed in Table 9, the cloud seeding program results in a notable rise in the flooding crop loss ratio by 0.54, around a 32% increase with a 99% level of significance. It is worth noting that the US crop insurance typically reserves a 12% premium for severe and unexpected disaster losses, a sum considerably lower than the observed increase. This suggests that the elevated flooding crop loss ratio could present challenges to the financial sustainability of crop insurance companies. In the long term, there may be implications for increased insurance premiums and subsidies.

The existing literature may provide evidence to support the crop flooding damage resulting from cloud seeding. Following cloud seeding missions for hail suppression, target areas tend to experience heightened precipitation of 10% to 12% (Spiridonov et al., 2015; Tuftedal et al., 2022). Furthermore, in cases where the cloud seeding mission is aimed at rain augmentation, the target areas often encounter even more substantial increases in precipitation. Drawing from experiences in other warm-season cloud seeding countries, Almheiri et al. (2021) conducted intensity-duration-frequency curves, revealing heightened rainfall intensities post-cloud-seeding missions and elucidating the potential reasons behind the significant urban inundation experienced by the United Arab Emirates in 2007 after seeding. Similarly, Yoo et al. (2022) observed a significant increase in runoff by approximately 60% in Korea following cloud seeding. In Texas, individual cells witnessed a 50 to 100% surge after seeding (Texas Natural Resource Conservation Commission, 1997).

Additionally, researchers assert that the speed at which rainfall occurs is understudied. In the natural environment, storms usually endure for only two to six hours, and rainfall or hail may fall steadily. However, experimental evidence suggests that cloud seeding can trigger the generation of more hailstones or rainfall within a 30-minute timeframe. This implies that precipitation is concentrated in a shorter duration, potentially explaining the elevated flooding crop loss ratio observed after cloud seeding programs.

I also explored whether cloud seeding contributes to increased crop production or crop yield by mitigating hail damage or enhance rainfall. Table 9 presents the impacts of cloud seeding on major crops, namely winter wheat, corn, and sorghum. Cloud seeding has no statistically significant effect on wheat or sorghum production in the target counties. However, there is a statistically significant increase of 17.82 bushels per harvested acre in corn yield, accounting for approximately a 15% increase. Conversely, in downwind counties, the spillover effect of the cloud seeding program results in a significant decline of sorghum productivity by approximately 10 bushels per harvested acre, reflecting a decrease of around 15%.

A potential explanation for these findings is that winter wheat can thrive in dryland conditions, but production and yield may decline when moisture levels are excessively high. These findings align with the patterns observed in Table 9. Also, less moisture as measured by the variable Dry significantly decreases production and yield on crops, but it affects wheat less than corn and sorghum. As anticipated, GDD contributes to increased crop production and yield, while SDD is linked to decreased production and yield. However, different crops exhibit varied responses to the Wet variable[38].

[38] Corn vs. Grain Sorghum in Water Limited Scenarios: https://www.cropquest.com/corn-vs-grain-sorghum/#

Table 9. Cloud seeding effects (Kansas sample)

	Weather variables			Crop loss ratio			Crop productivity		
	Hail frequency	Hail magnitude	Rainfall	Hail Loss ratio	Drought Loss ratio	Flooding Loss ratio	Wheat	Corn	Sorghum
Seed	-0.43 (1.13)	-0.10* (0.05)	0.26*** (0.08)	0.29 (0.26)	0.11 (0.13)	0.54*** (0.16)	-0.66 (1.52)	17.82*** (3.54)	-2.03 (2.41)
UWseed	2.55 (1.59)	0.10 (0.08)	-0.08 (0.11)	-0.18 (0.36)	0.20 (0.19)	0.11 (0.22)	-3.04 (2.23)	5.65 (5.05)	-9.98*** (3.36)
Wet	0.89*** (0.31)	0.02 (0.01)	0.81*** (0.02)	0.19** (0.08)	0.12*** (0.04)	0.24*** (0.04)	-0.69* (0.40)	0.44 (1.04)	3.74*** (0.77)
Dry	-1.79*** (0.45)	-0.06*** (0.02)	-0.50*** (0.03)	0.43*** (0.11)	0.65*** (0.05)	0.26*** (0.06)	-3.57*** (0.56)	-6.77*** (1.35)	-10.76*** (1.01)
GDD	0.0002 (0.001)	-0.00001 (0.00002)	0.0001*** (0.0001)	0.0001 (0.0002)	-0.0001 (0.0003)	-0.0001 (0.0001)	-0.0004 (0.0005)	0.004*** (0.001)	0.004*** (0.001)
SDD	0.0002 (0.0002)	0.0001 (0.0001)	-0.0002 (0.0002)	-0.00001 (0.001)	0.0003 (0.0003)	0.0005 (0.0003)	0.002 (0.003)	-0.04*** (0.007)	-0.034*** (0.005)
County Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square									
Within	0.195	0.056	0.789	0.210	0.509	0.163	0.386	0.565	0.712
Between	0.029	0.004	0.527	0.161	0.040	0.019	0.067	0.001	0.226
Overall	0.136	0.051	0.565	0.197	0.482	0.135	0.327	0.208	0.599
Observations	1,842	1,842	1,835	1,842	1,800	1,774	1,615	1,426	1,193

*:10%, **:5%, ***:1% statistic significant.

(2) Estimating the cloud seeding program impacts in West Kansas

The data used in the preceding estimations included all counties in Kansas. To ensure robustness, the analysis is revised to include counties adjacent to Kansas in Colorado and Oklahoma, forming control and comparison groups. To identify treated counties for the analysis, I utilized a logit model to predict the probability of counties adopting the cloud seeding program. The initial analysis focused solely on data from 2002, a year with a relatively high number of adopting counties compared to other years. In the logit model, variables such as downwind status, GDD, SDD, and the Palmer Z index were used to estimate the probability of adoption. The main difference arises from using the Palmer Z index rather than the Dry and Wet variables specified in the Data section (Section IV). This decision stemmed from the fact that 2002 experienced relatively dry conditions with lower moisture levels compared to normal conditions. Consequently, most of the Wet variables equated to zero, offering limited information due to the small sample size. Hence, I chose to utilize the Palmer Z index, the original variable employed in generating the Dry and Wet variables, in the logit model.

Based on the results of the logit model, I generated propensity scores for each county. Subsequently, I ranked each county by the propensity and matched one county that adopted the cloud seeding program to two counties that did not adopt the program but had similar propensity scores. In other words, within each matched group, these three counties exhibited similar tendencies to adopt the cloud seeding program. Consequently, I excluded counties that were not matched, as they might confound the results. After matching, 36 counties were included in the evaluation, primarily concentrated in the western part of Kansas, which is referred to as the West Kansas sample hereafter. In Figure 11, the counties shaded in orange indicate the West Kansas sample.

In the Table 10 weather variable columns, the cloud seeding program similarly shows no statistically significant impact on hailstorm frequency. In the West Kansas sample, the cloud seeding program increases hail magnitude in downwind areas by 0.11 inches, approximately 9%. In the appendix, Table A2 provides the results using all samples, including Kansas and adjacent counties, and the impact of cloud seeding program on hailstorm frequency and magnitude is both insignificant.

In short, these results are consistent with the literature; the evidence suggests that the cloud seeding program may not have a statistically significant impact on hailstorm frequency and magnitude, or the impact is negligible (Bergant, 2011; Gavrilov et al., 2013; and Rivera et al., 2020).

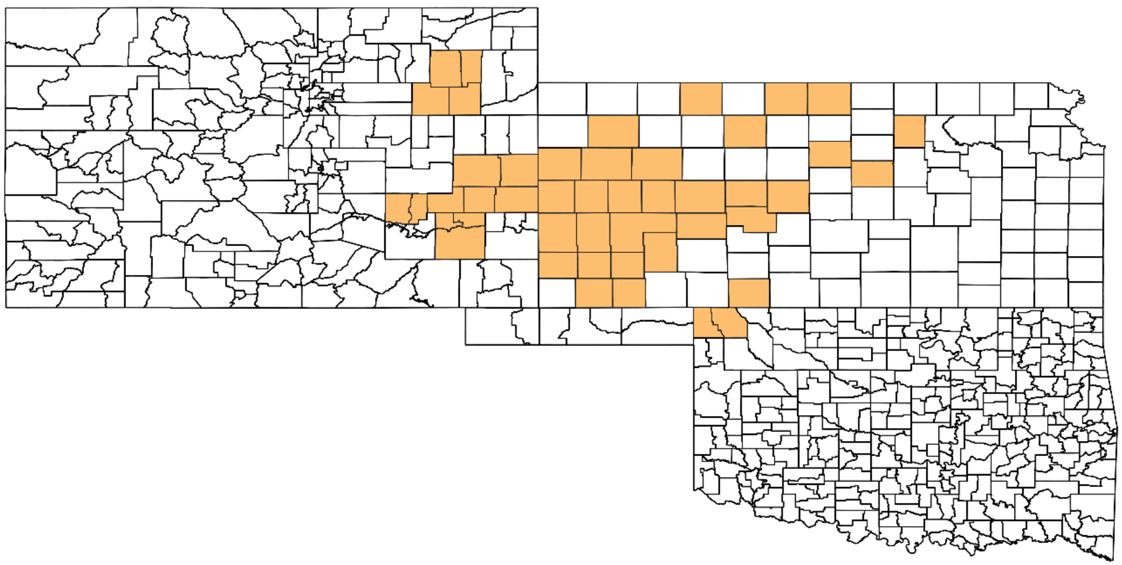


Figure 11. Kansas and West Kansas sample counties

In the Table 10 crop loss ratio column, despite the increase in hail magnitude due to the upwind cloud seeding program, the hail loss ratio does not exhibit a corresponding increase in the downwind areas. According to the results, the cloud seeding program is not statistically significant in the hail loss ratio regression. As observed in Table 9 crop loss ratio column, the cloud seeding program also raises the crop flooding loss ratio by 0.50 (31%). Less moisture, as indicated by Dry, increases the loss ratio of drought and flooding on crops. As mentioned earlier, intense precipitation is sometimes observed after seeding events, and the intense precipitation can cause flooding, especially if the soil is dry. Therefore, if the Dry indicator deviates more from normal weather conditions, damage to croplands is more likely when intense precipitation occurs[39].

The estimated effects of cloud seeding on crop productivity in Table 10 are similar to Table 9. The cloud seeding program improves corn productivity in the seeded area by 8.5 per bushel per harvested acre, around 7%. However, the magnitude in West Kansas sample

[39] See World Food Program "Why do floods follow droughts? Look to the Somali Region of Ethiopia". https://www.wfpusa.org/articles/floods-follow-droughts-ethiopia/

is smaller than the full Kansas sample. However, the cloud seeding program decreases sorghum productivity in downwind areas by 10.15, around 16%, which is similar to the result of full Kansas sample.

In conclusion, the evidence presented in this chapter provides some evidence that there is a statistically significant impact on hailstorm magnitude but not frequency. Moreover, I found no evidence that cloud seeding reduced hail and drought indemnities on crops. However, the analysis suggests that cloud seeding may have unintentionally resulted in increased losses from excess moisture (i.e. flooding) in seeding areas. Finally, the results suggest that there are spillover effects of the cloud seeding program on downwind areas, and the results are robust among different samples. Cloud seeding is associated with an increase in corn productivity in seeded areas and a decrease in sorghum productivity in downwind areas. These findings may be because corn favors more moisture, while sorghum is sensitive to excess moisture and flooding. While I found that the cloud seeding program has an impact on crop productivity, the mechanism might not be due to the beneficial competitiveness hypothesis but unintended changes in precipitation patterns, such as increasing intense rainfall.

Table 10. Cloud seeding effects (West Kansas sample)

Variable	Weather variables			Crop loss ratio			Crop productivity		
	Hail frequency	Hail magnitude	Rainfall	Hail Loss ratio	Drought Loss ratio	Flooding Loss ratio	Wheat	Corn	Sorghum
Seed	0.30 (1.10)	-0.03 (0.05)	0.02 (0.05)	0.24 (0.23)	0.03 (0.11)	0.50*** (0.18)	-0.71 (1.31)	8.50** (4.06)	-2.59 (2.46)
UWseed	3.15** (1.46)	0.12* (0.06)	-0.08 (0.06)	-0.17 (0.31)	0.13 (0.15)	0.06 (0.25)	-2.29 (1.81)	0.15 (5.47)	-10.19*** (3.27)
Wet	0.18 (0.44)	-0.03 (0.02)	0.20*** (0.02)	0.18* (0.09)	0.09* (0.04)	0.22*** (0.07)	0.39 (0.56)	2.70 (1.82)	4.61*** (1.06)
Dry	-1.44** (0.64)	0.01 (0.03)	-0.15*** (0.03)	0.06 (0.15)	0.50*** (0.07)	0.22* (0.12)	-2.28*** (0.78)	-8.13*** (2.31)	-10.15*** (1.49)
GDD	0.001 (0.001)	0.0001 (0.0001)	0.0002*** (0.0001)	-0.0002 (0.0003)	-0.0002 (0.0001)	-0.0002 (0.0002)	-0.003* (0.001)	0.005 (0.005)	-0.001 (0.003)
SDD	-0.001 (0.003)	-0.0002 (0.0002)	-0.001*** (0.0002)	0.001 (0.001)	0.001* (0.0004)	0.001 (0.001)	0.007 (0.004)	-0.026* (0.014)	-0.011 (0.008)
County Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square									
within	0.220	0.138	0.637	0.272	0.670	0.198	0.689	0.396	0.748
between	0.015	0.004	0.324	0.057	0.184	0.005	0.0004	0.117	0.127
Overall	0.173	0.114	0.241	0.239	0.612	0.160	0.539	0.147	0.538
Observations	638	638	641	617	615	587	498	454	466

*:10%, **:5%, ***:1% statistic significant.

(3) Cost-Benefit analysis of cloud seeding program

The cloud seeding program has two primary purposes: to preserve water resources in Western Kansas Groundwater Management District No. 1 and to reduce hail damage through rain enhancement and hail suppression. In the previous section, I presented evidence that the cloud seeding program increases precipitation by an average of 0.26 inches in target areas during the growing season. While this outcome generates a benefit from a water resource management perspective, the evaluation also shows that it raises crop loss ratios due to unintended flooding. Estimating the value of aquifer recharge falls beyond the scope of this research. Moreover, the flood damage to crops is already reflected in crop yield data; combining crop yields and flood damage into the cost-benefit analysis would result in double-counting.

According to Sophocleous (2015), farmers in western Kansas withdraw groundwater for irrigation at a rate 12 to 40 times greater than the rate of aquifer recharge. Additionally, the Kansas Department of Agriculture reports that approximately 85% of water discharge is used for irrigation[40]. Therefore, changes in productivity (e.g., corn yield) due to the cloud seeding program may serve as a proxy for the value of water resources and the damage caused by flooding. In the remainder of this section, I calculate the costs and benefits of the cloud seeding program from the perspective of both county and state governments.

(a) County Government

In the model presented in Section III, county government officials maximize net political benefits by deciding whether to participate in the cloud seeding program. County officials may choose to prioritize majority interest groups in the county to gain more votes. In counties that participate in the cloud seeding program, a major contribution to Gross Domestic Product (GDP) comes from the agricultural sector. The Regional Economic Analysis Project estimates Kansas's GDP by county from 2017 to 2022, indicating that in most counties involved in the cloud seeding program, over 40% of GDP is attributed to agriculture (see Figure 12). Therefore, it is rational for county government officials to make decisions that protect farmers' interests and gain their political support. Consequently, in the cost-benefit analysis conducted from the perspective of county government, the

[40] See the Kansas Department of Agriculture: https://www.agriculture.ks.gov/divisions-programs/division-of-water-resources/water-appropriation/water-use-reporting.

benefits of cloud seeding include increased productivity, while the costs involve spillover effects and expenses associated with the project.

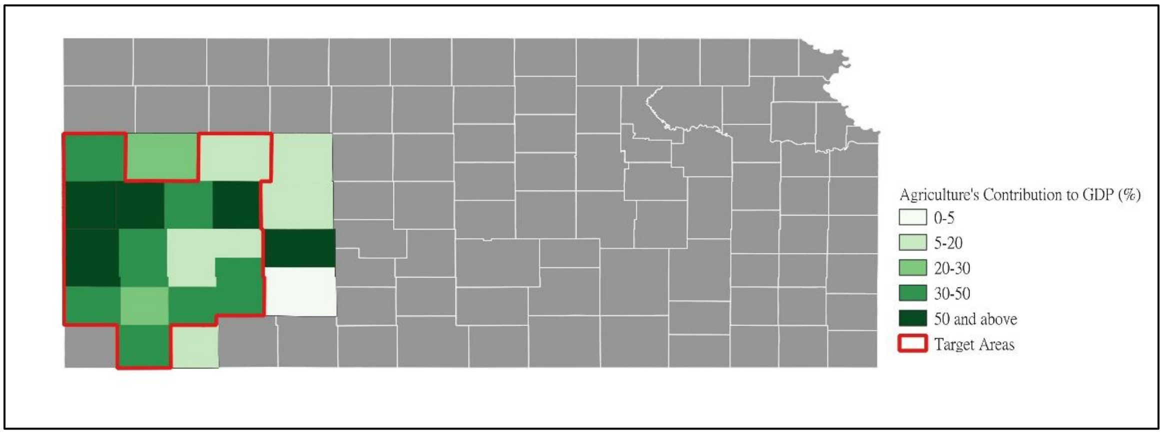


Figure 12. Agriculture's Contribution to County GDP (Percentage)

In Table 11, I present the net social benefit (NSB) for each county that participated in the cloud seeding program from 2002 to 2016, where NSB is equal to social benefits minus social costs. The values are expressed in real terms (2002 dollars), without discounting. This approach was chosen because county government officials typically make decisions based on one-year timeframes, often overlooking long-term benefits (the benefits of the program are realized in the following year, making the evaluation period relatively short). Furthermore, as noted by Boardman (2018), empirical evidence suggests that county governments are less concerned with discount rates when allocating budgets to projects[41]. I converted the costs and benefits for county governments from nominal to real terms using the Consumer Price Index, with 2002 as the base year.

In addition, the net present value (NPV) for each county is also provided. I use Equation (3) to estimate the present value of the net social benefits from the cloud seeding program, discounted back to 2002. NSB_t represents the net social benefit from the cloud seeding program during period t. The discount rate (r) used here is sourced from the Office of Management and Budget for 2002. To demonstrate that the overall assessment is not sensitive to the discount rate, I also apply a real discount rate of 3.1% for 10-year projects and 3.9% for 30-year projects.

[41] However, I also provided the Net Present Value, calculated using equation (3), in Table 5.

$$NPV = \sum_{t=0}^{T} \frac{NSB_t}{(1+r)^t} \tag{3}$$

The cost of the cloud seeding program encompasses both state and county government budgets. Data on the state government budget are taken from The Governor's Budget Report, focusing on the portion allocated to the Kansas Water Office for weather modification. County government budget information is obtained from the Kansas Department of Administration. For Gove, Haskell, and Wallace counties, where specific data are unavailable, the average expenditure across all participating county governments is used as a substitute. On average, each participating county contributed \$19,225 annually to finance the cloud seeding program. Consequently, the total annual cost of the cloud seeding initiative in Kansas amounts to approximately \$367,880, including variable and fixed costs.

The benefit of a cloud seeding program is the productivity gain in corn. However, the estimates indicated that the downwind counties experience a productivity loss in sorghum due to spillover effects, even after opting out of the cloud seeding program. Therefore, I calculate the cumulative benefit for each county over the entire period of cloud seeding program, from 2002 to 2016.

The benefit computation involves multiplying the yield gain and loss per acre by the total harvested acres in each county and the respective price per bushel of crops in Kansas. The yield changes attributable to the cloud seeding program are determined by the parameters estimated from Table 4, the productivity gain of corn is 8.5 bushels per acre and the productivity loss of sorghum is 10 bushels per acre[42]. These parameters serve as the basis for conducting the cost-benefit analysis for the affected counties. Key data sources for this analysis include the USDA National Agricultural Statistics Services, which provides information on the harvested acres of corn and sorghum in each county, as well as the prices of these crops. The price used here is the average crop price for the year[43].

[42] I also estimated the cost-benefit results using the parameters from Table 9: the productivity gain for corn is 18 bushels per acre, and the productivity loss for sorghum is 10 bushels per acre. Please see Table D1.
[43] The USDA NASS dataset provides monthly crop prices only, and the price used for the cost-benefit analysis is the average annual crop price.

Table 11. Net Benefit and Net Present Value of Counties Participating in the Cloud Seeding Program (2002–2016)

County	Number of years participating in program during 2002-2016	Net benefit (2002-2016) (real 2002 dollars)	Net Present Value	
			Real discount rate 3.1%	Real discount rate 3.9%
Finney	10	1,831,075	1,426,941	1,345,617
Gove	2	790,496	611,813	575,094
Grant	8	4,873,625	4,101,933	3,939,103
Gray	10	2,959,406	2,404,498	2,287,780
Greeley	6	6,189,554	4,649,501	4,331,813
Hamilton	11	5,506,160	4,586,679	4,393,534
Haskell	8	17,803,679	14,700,000	14,000,000
Kearny	13	2,015,673	1,382,509	1,252,628
Lane	14	-8,631,244	-7,137,036	-6,820,124
Scott	14	-2,517,396	-1,800,892	-1,657,309
Stanton	6	8,702,797	6,554,645	6,118,098
Stevens	2	4,375,014	3,237,275	3,001,360
Wallace	2	1,076,670	737,243	670,059
Wichita	11	7,220,984	5,869,599	5,571,474

Based year: 2002.

The resulting of the cost-benefit analysis are presented in Table 11. The benefits vary depending on the major crops in the county, the number of years participating in the program, and spillover effects from adjacent counties. Overall, the net benefits for most of the participating counties are positive, even with different discount rates. For example, Stevens County participated for two years, generating a net benefit of 4 million dollars. However, Lane and Scott Counties participated in the program over the entire period of analysis and experienced negative net benefits because of spill over effects on sorghum.

(b) State Government

The state government, rather than county governments, is responsible for investing in and maintaining the program's capital, such as radar systems, offices, and aircraft. In doing so, the state should also account for discounting the overall project. While county governments may focus on gaining political support within their jurisdictions, the state government must consider potential impacts on downwind counties that did not participate in the program but were still affected by seeding activity. These counties, which did not participate in the program, experienced downwind effects due to their proximity to the seeded areas. The externalities for these counties were included in the analysis.

Table 12 presents multiple sets of NPV estimates to show that the results are not sensitive to the choice of discount rates[44]. Counties not participating in the cloud seeding program but were affected by spillover effects experienced total losses of approximately \$30 million over the period. Participating counties, when accounting for the discount rate, gained around \$40 million. Although some counties showed a negative net present value, the overall benefit remains positive.

The Kansas Water Office estimated the return ratio of the cloud seeding program in six target counties in Kansas (Eklund et al., 1999). Their report concluded that the program reduced crop damage, resulting in a return ratio of 37 based on this reduction. Similarly, in a study by Knowles and Skidmore (2021), the cloud seeding program in North Dakota was found to generate a return ratio of around 37. In the present research, without considering downwind counties, the discounted net present value of the 14 Kansas target counties is \$41,324,710, while the discounted cost is \$4,098,507, resulting in a return ratio of approximately 10. However, when spillover effects are taken into account, the return ratio decreases to around 3. These results are consistent with past literature, which also reported positive return ratios for cloud seeding programs in Kansas and North Dakota.

Even with a favorable cost-benefit ratio, the state government still terminated the program. The potential explanation is that the state government is also pursuing political support based on the model in Section 3, but the spillover effects shown in Table 12 might result in disapproval in counties experiencing negative impacts.

[44] I also estimated the cost-benefit results using the parameters from Table 9: the productivity gain for corn is 18 bushels per acre, and the productivity loss for sorghum is 10 bushels per acre. Please see Table D2.

Table 12. Net present value of cloud seeding program in Kansas

	Net present value (2002-2016)	
	Real Discount Rates 3.1%	**Real Discount Rates 3.9%**
NPV (participating)	39,009,128	41,324,710
NPV (non-participating)	-28,031,183	-29,149,102
Overall	10,977,945	12,175,608

Base year: 2002.

V. Conclusion

Hail damage to agriculture often receives inadequate attention, particularly in regions like Kansas, where frequent hailstorms result in significant crop losses. To mitigate hail damage, the Kansas state and county governments implemented a cloud seeding program aimed at suppressing hail while also enhancing regional precipitation. This study examines the program's effectiveness using various measures, including its impact on hailstorm frequency and intensity, crop damage, and crop production, while accounting for potential spillover effects.

When using the frequency and intensity of hail to evaluate the efficacy of the cloud seeding program, my empirical findings indicate that the program lacks a statistically significant impact on reducing hail frequency and intensity, or the observed impact is negligible. This is consistent with empirical findings from Slovenia, Serbia, and Argentina (Bergant, 2011; Gavrilov et al., 2013; and Rivera et al., 2020).While the program decreased average hailstone size by about 8%, from 1.13 inches to 1.03 inches, the average size of the hailstones is still greater than 1 inch, which is considered a potentially harmful size by NOAA. This may explain why cloud seeding does not yield a statistically significant reduction in crop loss ratios associated with hail in this study. However, I also observed an increase in precipitation within targeted areas. Similarly, the analysis shows no evidence of reductions in crop loss ratios due to drought.

Interestingly, the evidence identifies an unintended consequence: the program is linked to an increase of approximately 32% and 35% in crop flood loss ratios in cloud-seeded counties, as revealed in both Kansas and West Kansas samples. This result aligns with previous findings showing that precipitation intensity often rises sharply following cloud seeding missions (Almheiri et al, 2021; Spiridonov et al., 2015; Texas Natural Resource Conservation Commission, 1997; Tuftedal et al., 2022; and Yoo et al. 2022). Additionally, flooding may result from seeding conducted after drought conditions, where overly dry soil is not able to effectively absorb water. I also examined potential downwind effects of the Kansas cloud seeding program. First, the evidence provides no support for a "rain theft" phenomenon among counties; when an upwind county participates in cloud seeding, downwind counties do not experience a change in rainfall during growing season. Second, cloud seeding may provide additional benefits such as increased rainfall or potential underground water recharge. The findings indicate that downwind counties experienced approximately a 15% loss in sorghum productivity, as evident in both the Kansas and West Kansas samples. Simultaneously, seeded counties experienced increased corn production of 15% and 8.3%.

The findings regarding crop productivity are robust, and the aggregate net benefit and net present value of the cloud seeding program are positive based on the estimations. However, the overall outcome may not be entirely advantageous, as the analysis presents potential unintended consequences. There are limitations of the study due to data constraints, specifically the absence of information on seeding dates and locations. Use of county level data, as reported in this chapter, could potentially lead to an overestimation of the impact of cloud seeding because hail damage is often localized, occurs in narrow, elongated zones rather than uniformly affecting the entire crop fields.

Given the vast expanse of cropland in the U.S., relying solely on crop insurance can impose significant financial burdens on both farmers and taxpayers[45]. Another alternative, such as anti-hail nets (Gandorfer et al., 2016; Porsch et al., 2018; Rogna et al. 2021; Rogna et al., 2022), are not feasible for large-scale farms or ranchers due to their cost and practicality, , and large hailstones can still penetrate these nets (Childs et al., 2020)[46].

Cloud seeding remains a promising approach for reducing hail damage across extensive agricultural areas. First, advancements in technology, such as the use of uncrewed aircraft systems, have the potential to improve the efficiency and effectiveness of seeding operations (DeFelice et al., 2023). Second, future discussions should focus on optimizing project design and addressing spillover effects. Introducing a compensation mechanism for affected areas could mitigate negative externalities and enhance the program's sustainability. More research is needed to better understand the efficacy of cloud seeding and its broader impacts. Continued exploration of this technology is vital for developing innovative, cost-effective solutions to mitigate hail damage and support the agricultural sector.

[45] On average, producers only pay 40% of the premium, see: https://www.ers.usda.gov/topics/farm-economy/farm-commodity-policy/title-xi-crop-insurance-program-provisions/

[46] Average farmland sizes are 60 ha and 11 ha in Germany and Italy, respectively. In the USA, the average farmland size is 445 ha, and it might be the reason why farmers could not establish anti-hail net. Therefore, cloud seeding might be a more cost-efficient way to avoid hail damage.

CHAPTER 3: Factors influencing policy termination

I. Introduction

Hailstorms have caused economic losses of approximately $35.8 billion in the United States (US) over the past two decades (NOAA, 2024). Weather modification, specifically cloud seeding, is a promising tool to mitigate hail damage as well as alleviate drought[47].

According to the National Oceanic and Atmospheric Administration (NOAA), Kansas, Oklahoma, and Texas are among the most hail-prone areas in the US[48]. Due to this exposure, Kansas adopted cloud seeding from 1975 to 2016 for both hail suppression and rain augmentation. While the state government provided funding for the weather modification program, it required financial sponsorship from county governments to provide radar, pilot and aircraft, and seeding material. County government officials could then decide whether to participate in the program, which required budget allocations based on population size.

According to NOAA's weather modification report, the number of county governments participating in the program steadily decreased each year from 2002 until the state government suspended the program in 2016 due to tight funding. Also, during the 2002 to 2016 period several counties opted out and later rejoined the program. These observations suggest that there might be other potential factors influencing cloud seeding program termination decisions. For example, in the late 1990s farmers in Southeast Colorado expressed a concerns that cloud-seeding makes more hail for areas next to the targeted zones[49]. In the early 2000s, farmers in Kansas stated: "*We don't question that cloud seeding is reducing hail. We just want to make sure it's not hurting the total precipitation in our area*[50]." These concerns led farmers in northwest Kansas to form a grassroots organization, Citizens for Natural Weather, to oppose the cloud seeding. This background information suggests that there are a variety of potential factors that may influence decisions at the local level to exit the cloud seeding program; this paper offers an

---

[47] The principle of cloud seeding involves injecting fine particles into clouds to stimulate the hailstone, rain, or snow generation process. The goal of cloud seeding in Kansas generate smaller hailstones and/or increase rainfall.
[48] See Severe Weather Maps, Graphics, and Data Page from NOAA: https://www.spc.noaa.gov/wcm/index.html#data
[49] See: https://www.chieftain.com/story/special/1997/03/01/kansas-cloud-seeding-plan-worries/8762492007/
[50] From Kansas State Historical Society dataset: https://kansashistoricalopencontent.newspapers.com/

investigation of these potential factors.

Relative to analyses of policy adoption decisions, the research on policy termination is scarce. Policy termination theory emerged in the late 1960s to define policy termination, explore its rarity, and establish a theoretical framework. By the early 2000s, policy makers in debt burdened industrialized countries sought guidance regarding the conditions for terminating public investments and focused on the determinants of policy termination (Bauer, 2009; Ferry and Bachtler, 2013). Case studies dominate empirical research on policy termination, covering topics such as international trade (Rhee and Jang, 2022), tax incentives (Thom, 2021), regional development (Ferry and Bachtler, 2013), climate policy (Krause et al., 2016), and wage laws (Hwang, 2021). However, only one paper examines policy termination in the context of disaster risk reduction: termination of the face mask policy in the U.S. (Wang and Liu, 2024).

Disaster risk reduction policies are designed to enhance social, economic, and environmental resilience[51]. The goal of this paper is to investigate the potential factors influencing cloud seeding program termination decisions at the county level, thereby helping to address a gap in the research on policy termination within disaster risk arena. Moreover, discussions on policy termination often focus on national or state-level suspensions, with only a few papers examining decision-making processes at the local government level (Krause et al., 2016; Lamothe and Lamothe, 2015). This paper also aims to fill the gap by providing insights into the local government decision-making processes.

Specifically, in this paper cloud seeding program termination decisions by Kansas county government officials are studied. The empirical analysis begins with a Logit model to explore factors associated with the participation of the cloud seeding program over the 2002-2013 period. In addition, a Cox proportional hazard model is used to assess potential factors influencing the termination decision-making process. The present study examines four hypotheses derived from policy termination theory: fiscal stress, project efficacy, the diffusion effect, and political ideology. Each of these hypotheses is discussed in greater detail in the body of the paper.

[51] See the explanation from United Nations Office for Disaster Risk Reduction: https://www.undrr.org/terminology/disaster-risk-reduction

As a prelude to the full set of findings, the Logit analysis reveals county characteristics the influence the likelihood of county participation in the cloud seeding program: counties experiencing more frequent hailstorms, with higher levels of Republican support, and surrounded by neighboring counties that use clouding seeding are more likely to participate in the program. The Cox proportional hazards model offers an evaluation of factors influencing program termination among those counties that participated in the program. This evaluation indicates that among counties that adopted the cloud seeding program, termination is more likely in a county that experienced higher hail damage/losses in the previous year. Counties are also more likely to terminate the program if neighboring counties adopt cloud seeding, possibly due to the rapid spread of hailstorms across multiple counties, which may generate a free rider problem. Interestingly, fiscal stress and political ideology did not show significant influence on the likelihood of program termination.

The remaining parts of this paper are as follows: Section II provides background on the Kansas cloud seeding program. Section III reviews the literature on policy termination and presents a more detailed discussion of the hypotheses examined in this paper. Section IV and V present the data and empirical strategy, respectively. The results and conclusions are demonstrated in Section VI and VII.

II. History and background of cloud seeding programs in Kansas

The cloud seeding program in Kansas serves dual purposes, focusing on both hail suppression and rain augmentation, where hail suppression generally takes precedence over rain augmentation. Operational records indicate that from 2002 to 2016, cloud seeding days were allocated 65% for hail suppression and 35% for rain augmentation.

It is not a coincidence that counties adopting the cloud seeding program are concentrated in western Kansas (See Figure 13). Annual precipitation in western Kansas ranges from 13 inches to 30 inches, while in eastern Kansas it ranges from 30 inches to 50 inches. Additionally, Kansas' elevation rises from east to west, with the highest elevations exceeding 4,000 feet and the lowest near 700 feet above sea level in eastern Kansas. Elevation is closely related to hailstorms and potential hail damage. The freezing level in convective cloud systems is closer to the ground in higher elevation regions. Consequently, even less intense thunderstorms can produce hail because the relatively high elevation creates a natural freezing level for thunderstorms. Furthermore, hailstones can remain at the freezing level longer and grow larger. Hailstones of over 1 inch in size can potentially cause damage. To summarize, , western Kansas experiences dry conditions and frequent hailstorms.

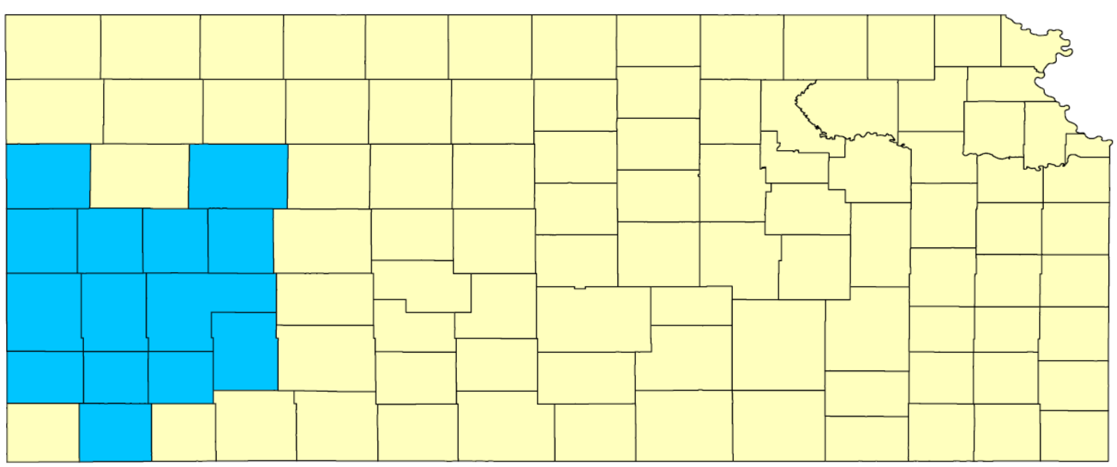


Figure 13. Map of counties participating in the cloud seeding program (2002, Kansas)

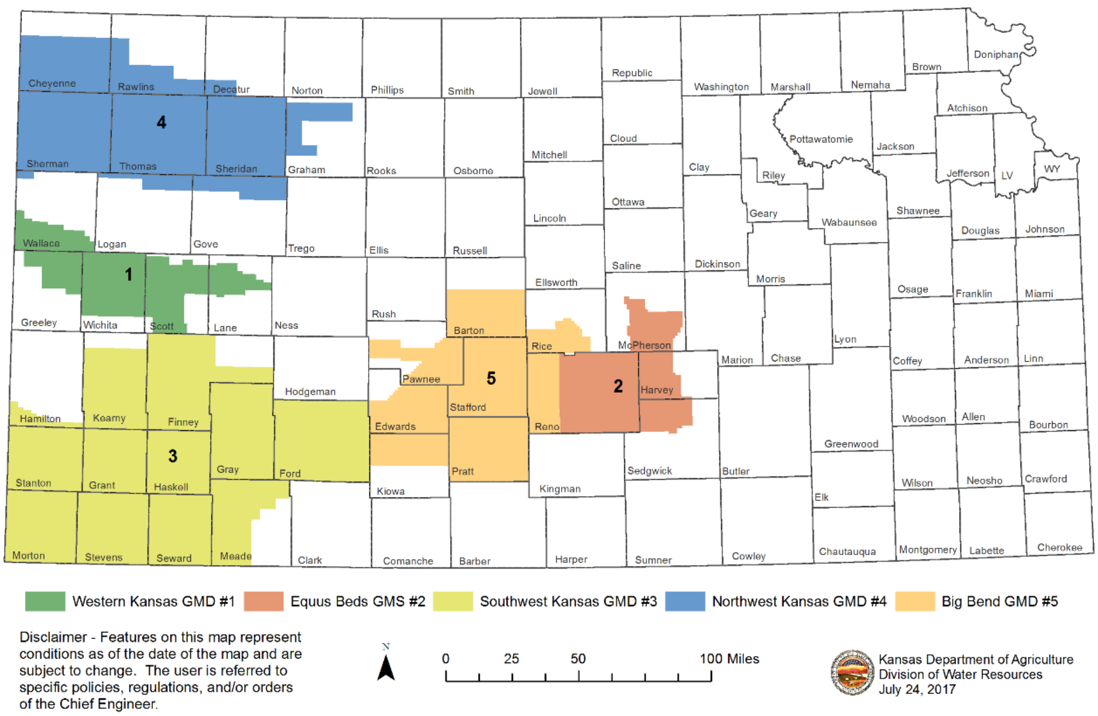
In 1972, severe drought damaged Western Kansas agriculture, prompting local governments to request state intervention. The State Finance Council approved $100,000 in emergency funds to implement cloud seeding in northwest Kansas for drought relief. The Kansas Water Resources Board worked with the U.S. Bureau of Reclamation to oversee the cloud seeding pilot project. However, before the project could be executed, moisture conditions improved, shifting the project's goal to experimenting with cloud seeding in nature.

Colby City in northwest Kansas conducted the first cloud seeding experiment in 1972 over a nine-week period. In 1973 and 1974, four counties joined the pilot project. The Kansas Water Resources Board published special report, which stated: "*The fact that a portion of the funds supporting the Kansas cumulus projects came from county sources was an indication of at least localized interest in operational cloud seeding*[52]." Increasingly, county governments showed their support: After the Kansas Weather Modification Act passed in 1974, eleven counties applied for permits and licenses to operate cloud seeding programs.

Residents in the county expressed their opinions to county commissioners about sponsoring the program. The county commissioners then voted and allocated funds in the following year. The agency operating the cloud seeding program in the region was the Western Kansas Groundwater Management District No. 1 (GMD1, see Figure 14). In each year of the program, GMD1 held an annual meeting to promote the cloud seeding program. In 2012, GMD1 supported the weather modification program[53], but also provided extra funding of $20,000 to each participating county[54].

---

[52] See the reference Kostecki (1977).
[53] State government provides support for the most expensive part of the program, including a highly sensitive radar system, telecommunications, and a data link for computing.
[54] See https://www.cjonline.com/story/news/politics/state/2012/09/04/drought-hurting-kansas-programs-rain-effort/16422352007/



Source: Kansas Department of Agriculture, see: https://agriculture.ks.gov/divisions-programs/dwr/managing-kansas-water-resources/groundwater-management-districts

Figure 14. Groundwater Management Districts in Kansas

However, members of the public have different opinions about cloud the seeding program. In the November 28, 1994 edition of the Council Grove (Kansas) Republican[55], an article stated: "*Officials at the Kansas Water Office in Topeka want Kansas taxpayers to give them $390,000 to mess with nature.*" The same article quoted Cloud seeding project Manager Keith Lebbin "*Who doesn't mess with Mother Nature? If you have a section of land and grow anything but buffalo grass, you're messing with Mother Nature. Every time you start your car, you're messing with Mother Nature.*"

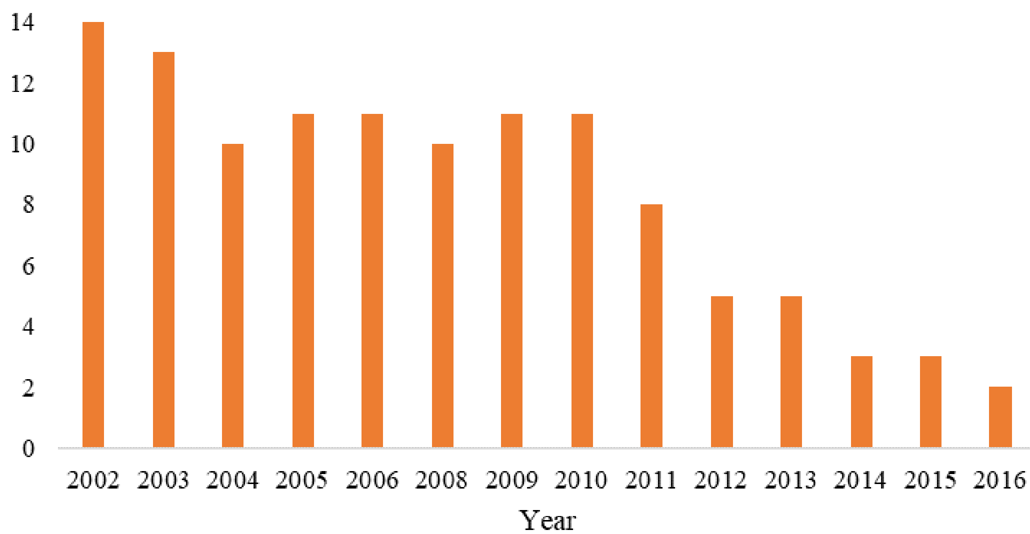
In addition to ethical questions, there are also practical concerns about the cloud seeding program. The Groundwater Management District Number 4 (GMD4) held 20 public meetings to launch a five-year cloud seeding program starting in April 1997 (see Figure 2). However, opposition to cloud seeding among farmers in the region was evidenced by the formation of an organization called Citizens for Natural Weather.

[55] From Kansas State Historical Society dataset: https://kansashistoricalopencontent.newspapers.com/

According to a newspaper article dated May 18, 1998[56], the farmers stated: "*We don't question that cloud seeding is reducing hail. We just want to make sure it's not hurting the total precipitation in our area.*" In 1999, counties within GMD4 opted out of the weather modification program. Moreover, Rawlins County sued GMD4, challenging the authority of the local government.

Based on research by the Kansas Water Office, the benefit-cost ratio of the cloud seeding program is 37:1[57]. This ratio indicates that an investment of one dollar can generate an additional 37 dollars in crop yields for the sponsoring counties, excluding other potential benefits. Despite evidence of the program's high return on investment, it was suspended in 2016. The stated reason for suspension was a tight Kansas Water Office budget[58].

Moreover, even though the cloud seeding program is highly subsidized, the number of participating counties decreased from a maximum of 17 to just 2 before the state halted the program, as shown in Figure 15.



Data source: NOAA.

Note: In total, there are 105 counties in Kansas. 2007 data is missing.

Figure 15. Numbers of counties participating in Kansas cloud seeding program

[56] From Kansas State Historical Society dataset: https://kansashistoricalopencontent.newspapers.com/

[57] See the webpage of WKGMD#1: https://www.gmd1.org/weather-program/.

[58] See the webpage of WKGMD#1: https://www.gmd1.org/weather-program/.

III. Policy Termination and Hypothesis

Relative to extensive analyses of policy adoption decisions, the research on policy termination is scarce[59] (DeLeon, 1978) and understudied (Geva-May, 2001; and Lamothe and Lamothe, 2015). DeLeon (1978) defined policy termination as the complete cessation of functions, programs, organizations, and projects by the government. However, there is still some debate about the concept of policy termination, as policies may not be terminated entirely but rather modified or adjusted in different forms (Hogwood and Peters, 1982).

DeLeon (1978) categorized two types of policy termination: strict termination and partial termination. Strict termination means that the functions, programs, and projects of the government stop and cease entirely. There are two extreme cases of strict policy termination: the first is when the policy has fully achieved its goals and is no longer needed; the second is when the policy exacerbates the situation and is terminated. Partial termination involves reconsidering the policy due to redundancy, obsolescence, or dysfunction, and then terminating or revising government functions, organizations, programs, or policies. Partial termination is equivalent to policy adjustment or policy succession (Hogwood and Peters, 1982; and Ferry, 2013).

In the context of the cloud seeding program in Kansas, neither state nor county governments have used the program since 2016. Moreover, as of 2023 Kansas is no longer a member of the North American Weather Modification Council. Although the Kansas government has not abrogated the Weather Modification Act, the Kansas cloud seeding program was effectively terminated at the state level after 2016. Note also that prior to 2016 a number of county governments halted their participation in the program.

However, cloud seeding program termination does not fully align with the description of strict termination. First, it is impossible for a risk reduction policy to fully achieve its goal of fully eliminating natural disaster risk and thus be no longer needed. Second, there is no strong evidence that the cloud seeding program exacerbated hail damage, although most farmers were concerned about spillover effects such as decreased precipitation. On the other hand, the cloud seeding program also does not meet the definition of partial termination, as there is no similar program to replace weather modification for hail

[59] A simple keyword search in the Web of Science Core Collection yielded 79,471 results for policy adoption and 3,052 results for policy termination.

suppression purposes.

Although there are gaps in the theory, the focus of policy termination research has shifted from establishing a general policy termination theory to identifying the determinants of policy termination due to practical needs (Ferry and Bachtler, 2013). More importantly, the understudy of policy termination is at least partly due to its infrequent occurrence (Bardach, 1976), which has led most termination studies to concentrate on qualitative case studies or perspective analysis (Lamothe and Lamothe, 2015).

Lamothe and Lamothe (2015) were the first to combine policy termination theory with policy diffusion theory and the make-and-buy concept from a different literature, providing a quantitative analysis. This work has inspired the emergence of more quantitative research on policy termination (Li, 2017; Miao, 2019; Hwang, 2021; Rhee and Jang, 2022), with empirical studies employing various theories from different fields depending on the policy context (see Table 13).

Table 13. Related theories and potential factors/pathways

Theory	Potential factors or pathways
Policy termination theory (Kaufman, 1976; deLeon, 1978)	• Fiscal stress • Political ideology • Program effectiveness • Interest group influence
Policy diffusion theory (Berry and Berry, 2014; Li, 2017; Hwang, 2021)	• Regional diffusion (Neighbors) • Leader-laggard diffusion (innovation) • Vertical diffusion (Federal/State/County)
Policy entrepreneur literature (Geva-May, 2004; O'Neill et al.; 2018; Hatch and Mead, 2021;)	• Entrepreneur can reduce the cost of government learning new knowledge
Public choice theory (Tiebout, 1956)	• Redistributed services • Services delivered by special districts
Make-or-Buy Literature (Geva-May, 2001; Lamothe and Lamothe, 2015)	• Cost of termination (financial, political, emotional, or legal) • Transaction cost (provide service by contract with the third party) • Previous Service delivery modes (private for profit company or market)
Hettich and Winer	• Political support and economic foundation of tax structure

Based on the literature and the context of cloud seeding in Kansas, I propose four hypotheses that might influence the termination decision.

(1) Fiscal stress

Fiscal stress is a factor influencing county government decisions to terminate policies (DeLeon, 1983). When faced with a tight budget, the government official might have the incentive to terminate policies or cut back budgets to reduce expenditure and save money (Kirkpatrick et al., 1999). Some empirical research indicates that governments with poor fiscal health tend to terminate public services (Graday and Ye, 2008). However, more empirical findings show that fiscal stress does not play a significant role in policy termination (Volden, 2010; Krause, 2016; Hwang, 2021).

In the case of the cloud seeding program, it was stated that GMD1 ceased operations due to a tight budget. However, for county governments, the cloud seeding program is highly subsidized, making it unlikely to be terminated unless local fiscal stress is severe and other services must be prioritized.

Hypothesis 1: The probability of terminating the cloud seeding program increases if the local government faces fiscal stress.

(2) Political ideology

Political ideology often plays a dominant role in determining a policy's continuation or termination (deLeon, 1983, 2002; Volden, 2010). First, the current party might want to terminate existing policies if they have an opposing political affiliation (Bardach, 1976; Berry et al., 2010; Birchall, 2014; Ragusa, 2010). Second, different parties or political affiliations have different preferences, such as being more conservative or more welcoming of emerging ideas and new technology. Empirical studies have discussed how political ideology affects the termination of face mask policies during COVID-19 (Wang and Liu, 2024) and policies related to extreme weather events (Gould et al., 2024). Conversely, policymakers may try to maintain the status quo and prevent the termination of current or existing decisions, which might be linked to concerns about failure or incompetence (Dür, 2001; Thom, 2020).

In Kansas, most counties support the Republican Party, but the level of support varies between counties. This variation might influence decisions to terminate the cloud seeding program.

Hypothesis 2: The probability of terminating the cloud seeding project increases if the political party affiliations are more conservative.

(3) Program effectiveness

The goal of government is to provide effective programs and policies to improve social welfare. Therefore, it seems straightforward to terminate a policy if it proves ineffective (deLeon, 1983; Turnhout, 2009). However, there are three reasons why a policy might not be terminated even if the program is inefficient. First, many public policies are ineffective due to political inefficacy (Shipan & Volden, 2008), meaning governments lack the capability to implement well-designed policies, sometimes turning them into harmful ones (Khoshnevis and Chelleri, 2018). Therefore, most governments prefer to keep the program and improve implementation efficiency rather than terminate existing policies. Second, policy evaluations are rarely purely objective, and many factors can undermine the credibility of evaluations (Thom, 2021). Kasdin and McCann (2019) surveyed federal governments and found that the probability of terminating low-effectiveness programs is not higher than for those rated highly effective. Moreover, from the sponsor's perspective, program ineffectiveness is the main reason for termination, but from the non-sponsor's point of view, effectiveness of the program is often irrelevant to policy termination. Finally, in the literature, while program effectiveness may be a crucial factor, the complexity of policies, especially high-level policies that encompass multiple programs, makes it difficult to use a single index or perspective to assess program effectiveness or agency performance (Krause, 2016; Thom, 2021).

The evaluation of the efficacy of cloud seeding programs, particularly in reducing hail damage, remains controversial. In the literature, two main approaches are used to measure the efficacy of cloud seeding programs. The first involves measuring differences in hailstorm frequency and magnitude (Bergant, 2011; Changnon, 1971; Dessens et al., 2016; Gavrilov et al., 2013; Rivera et al., 2020; Spiridonov et al., 2015). The second approach measures reductions in crop loss or increases in crop yield, with empirical research demonstrating significant reductions in crop damage due to cloud seeding (Federer et al., 1986; Ekland et al., 1999; Knowles and Skidmore, 2021; Abshaev et al., 2023). The impact of program efficacy on the decision to terminate cloud seeding programs remains unclear.

Hypothesis 3: The probability of terminating the cloud seeding program increases if county government officials and/or their constituents perceive the program to be ineffective.

(4) Policy diffusion

The definition of policy diffusion is "one government's policy choices being influenced by the choices of other governments" (Shipan and Volden, 2012; Lamothe and Lamothe, 2015). The influence diffuses through three major channels: learning, competition, coercion, or fulfilling norms and standards, with the first two being core mechanisms (Shipan and Volden, 2012; Berry and Berry, 2014; Miao, 2019).

However, governments can easily be influenced by neighboring jurisdictions (Walker, 1969) because counties that share a border often have frequent interactions when making decisions. Moreover, they may face similar challenges, such as hail damage or drought, and share similar socioeconomic or political profiles. Therefore, neighboring counties' decisions may also be suitable for themselves (Miao, 2019). Studies have found that neighbors' decisions influence the likelihood of policy termination (Lamothe and Lamothe, 2015; Li, 2017; Hwang, 2021; Thom, 2021).

In Kansas, counties that adopted the cloud seeding program are concentrated in the western part, as mentioned in Section II. From an operational standpoint, if most counties do not contribute to the program, its efficacy might diminish, rendering the public budget spent in vain (Boyce, 2000). Such a scenario was described in the final report of the Kansas cloud seeding program:[60] "*...most programs resulted in too many storms on active seeding days, indicating the need for additional aircraft.*" Therefore, termination decisions in these counties might be influenced by their neighbors' decisions regarding program efficacy.

Hypothesis 4: The probability of terminating the cloud seeding project increases if the number of border counties also abandon the cloud seeding program.

[60] Please see the report from Kansas State University extension, page 3. https://www.ksre.k-state.edu/irrigate/oow/p97/BossertWeatherModification.pdf

IV. Data

To test the hypothesis outlined in the preceding section, I utilize Kansas county-level data to investigate the factors that influence county participation as well as the termination decision-making process of the cloud seeding program. Owing to data constraints where data spanning from 2003 to 2013 is accessible, I examine program participation and termination for county governments. I compile a variety of datasets, and the summary of variables along with their respective data sources are provided in Table 14, while Table 15 presents summary statistics.

Table 14. Definition of variables and data sources

Variables	Description	Data source
Participate	0 and 1. If the county sponsors/participates cloud seeding program in year t, then 1, and 0 otherwise.	NOAA weather modification report.
Termination	0 and 1. If the county terminate cloud seeding program in year t, then 1, and 0 otherwise.	NOAA weather modification report.
Fiscal stress	Percentage change in county government revenue between year *t* and year *t-1*	The government's budget report (Kansas State)
Republican	Percentage of county *i* voting Republican Party in General election statistics for US Senator/President	Kansas Statistical Report
Loss_hail	Loss ratio of hail on crops at year *t-1*	USDA
Loss_drought	Loss ratio of drought on crops at year *t-1*	USDA
Loss_flood	Loss ratio of flood on crops at year *t-1*	USDA
Frequency	Number of hailstorms in county *i* at year *t-1*	NOAA
Magnitude	Average size of hailstone in county *i* at year *t-1* (inch)	NOAA
Neighbor	Percentage of neighbor counties, which sharing a boarder with county *i*, terminate cloud seeding program in year *t-1*	NOAA weather modification report.
Education	Percentage of population in county *i* with bachelor degree in year *t-1*	Kansas Statistical Report

Data on cloud seeding participation originate from the NOAA Weather Modification Report[61]. Regarding the Participate variable, a value of 1 indicates that the county participates in a cloud seeding program, while a value of 0 denotes otherwise. Similarly, the Terminate variable is created with a value of 1 indicating that the county has terminated its cloud seeding program, and 0 otherwise. The participation analysis includes all Kansas counties, whereas termination analysis excluded counties that never participate in the program. Throughout the period of analysis, approximately 9.4% of observations indicate participation in cloud seeding programs.

Utilizing the same dataset, I introduce the Neighbor variable, representing the percentage of adjacent counties that terminated their cloud seeding programs in the preceding period t-1. This variable is expressed in percentage terms rather than as a count of adjacent counties to account for variation in the number of adjacent counties each county may have (Berry and Berry, 1990; Hwang, 2021). On average, 90.9% of adjacent counties that participated in the cloud seeding program ultimately halted the participation. The capture the political ideology, I used the percentage of votes to Republican Party in General election statistics for US Senator/President. On average, the percentage of vote for Republican Party is 70.5%, which means in every election, about 70.5% of voters in the county voted to Republican Party.

Fiscal stress is gauged by the percentage change in county government revenue from year *t* to *t-1*. I refrained from employing the direct expenses of the cloud seeding program as a proxy for fiscal stress since they represent only a minor fraction of a county government's budget. On average, each participating county allocated $19,225 towards financing the cloud seeding program in a year. In Table 15, the average change stands at 5.2%, indicating an average annual increase in total county government revenue. Nonetheless, some counties encountered significant fluctuations, with decreases or increases of approximately 50%.

As discussed in the preceding section, assessing the efficacy of programs is often debated. Hence, I employ several variables to gauge the efficacy of the cloud seeding program. Firstly, local governments may be cognizant of the frequency and severity of

[61] According to Federal Law, all weather modification activity should submit report to NOAA.

hailstorms. Higher occurrences of hail or significant damage from drought could potentially influence their decisions regarding program participation. To represent the frequency and severity of hailstorms, I utilize the number of hailstorms that occurred in county *i* in year *t-1*, as well as the average size of hailstones in county *i* during the same period. On average, each county experiences 12 hailstorms annually, with a maximum of 83 occurrences in a single year. Regarding hailstone size, a county typically encounters hailstones measuring 1.12 inches, surpassing the 1-inch threshold known to cause damage. Secondly, local governments may take into account crop losses resulting from extreme weather events, which could be associated with the cloud seeding program. These events include hail damage, drought, and flooding. To capture crop losses, I utilize the loss ratio of crop insurance attributed to hail, drought, and flood events.[62].

Additionally, I control for education level, where, on average, 19.4% of the population within a county holds a college degree. These data were sourced from the Kansas Statistical Abstract.

Table 15. Summary statistics

Variable	Observation	Mean	Std. dev.	Min	Max
Sponsor	1,040	0.094	0.292	0.000	1.000
Fiscal stress	832	0.052	0.185	-0.711	2.977
Republican	1,040	0.705	0.086	0.458	0.901
Loss_hail	936	2.570	1.885	0.000	11.454
Loss_drought	917	2.704	1.231	0.000	7.856
Loss_flood	886	1.732	1.023	0.221	8.829
Frequency	918	12.841	9.579	1.000	83.000
Magnitude	918	1.128	0.226	0.750	2.542
Neighbor	1,040	0.909	0.215	0.000	1.000
Education	1,040	0.194	0.060	0.106	0.516

Note: There are negative loss ratio in the dataset, I adjust the negative value to zero.

[62] Loss ratio is insurance indemnity divided by total premiums.

V. Modeling and empirical strategy

In this paper, two empirical approaches are used to test the hypotheses. First, a Logit model is employed to investigate the factors associated with cloud seeding program participation. Second, a Cox proportional hazards model is used to examine factors influencing cloud seeding program termination.

(1) Logit model

In the literature, logit models have been used to investigate potential factors associated with policy adoption (Li, 2017; Miao, 2019) and termination (Lamothe and Lamothe, 2015; Krause, 2016). In this research, I use a logit model to explore the characteristics of counties and their correlation with participation in the cloud seeding program.

The conditional probability of participating in the cloud seeding program is denoted by $\Pr(Y = 1|\boldsymbol{x}) = \pi(\boldsymbol{x})$. And the multivariable logit regression model is given by the equation (1) (Hosmer et al., 2013).

$$g(\boldsymbol{x}) = \ln\left(\frac{\pi(x)}{1-\pi(x)}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots + \beta_m x_m + \varepsilon \quad (1)$$

In this paper, the specifications as equation (2), the estimated logit as follow:

$$g(\boldsymbol{x}) = \beta_0 + \beta_1 Fiscal\_Stress_{it-1} + \beta_2 Efficacy_{it-1} + \beta_3 Neighbor_{it-1} + \beta_4 Republican_{it-1} + \beta_5 Education_{it-1} + \varepsilon \quad (2)$$

In equation (2), all covariates are lagged by one period. This is because county governments must pass the budget before seeding the clouds during the growing season; therefore, their decisions are likely influenced by information from the previous year. The covariates are thoroughly described in the relevant previous section, with the exception of Efficacy, which is represented by a different proxy as discussed in the preceding section.

(2) Proportional hazards model

Survival analysis has been used to study political events such as policy termination and factors associated with their occurrence (Baybeck et al., 2011; Box-Steffensmeier and Jones, 2004; Li, 2017; Hwang, 2021). The hazard rate in survival analysis indicates the rate at which units experience a political event, considering both the duration spent in the initial state and the transition to a subsequent state (Box-Steffensmeier and Jones, 2004).

Survival analysis, or event history analysis, employs various methodologies, with the most common being the investigation of the duration of survival time before experiencing an event using a proportional hazards model. The assumption of the probability of hazard, $\mathrm{h}(t|\boldsymbol{x})$, is a proportion of time passed.

$$\mathrm{h}(t|\boldsymbol{x}) = h_0(t)exp(\beta\boldsymbol{x})$$

$h_0(t)$ is the baseline hazard rate, which means the county has a certain underlying probability of terminating the program. The Cox model is a semi-parametric model that does not specify the baseline hazard (Cox, 1972).

Wang and Yao (2023) introduced the application of the Cox proportional hazards model with covariates that vary over time. Under the Cox model, the probability for county *i* to terminate the cloud seeding program at period *t* is given by:

$$\begin{aligned} Termination_i(t) \\ &= h_0(t) \cdot \exp\,(\beta_1 Fiscal_{i,t-1} + \beta_2 Republican_{i,t-1} + \beta_3 Neighbor_{i,t-1} \\ &+ \beta_4 Diffusion_{i,t-1} + \beta_5 Education_{i,t-1}) \end{aligned}$$

The dependent variable *Termination* is 1 if county *i* terminates the cloud seeding program in period *t*. $Fiscal_{i,t-1}$ is the fiscal stress of county *i* in period *t-1*. $Ideology_{i,t-1}$ is the political ideology of county *i* in period *t-1*. $Efficacy_{i,t-1}$ is the efficacy of cloud seeding project of county *i* in period *t-1*. $Diffusion_{i,t-1}$ is the percentage of neighborhood of county *i* in period *t-1* which terminate cloud seeding policy. β_1 to β_5 is the hazard ratio I am interested in estimating.

In the Cox proportional hazards model, a hazard ratio larger than one is defined as a positive coefficient, indicating that with a change in the covariate, the risk of termination is increased. Conversely, a coefficient smaller than one is defined as a negative coefficient, indicating that with a change in the covariate, the risk of termination decreases. For example, if β_1>1, it indicates that an increase of one unit in fiscal stress increases the likelihood of a county terminating the cloud seeding program.

VI. Results and discussion

This section provides the empirical results accompanied by a discussion of findings.

(1) Empirical results of policy participation

Table 16 presents the Logit model results, highlighting factors associated with participation in cloud seeding programs: those with high hailstorm frequency, strong Republican Party support, and with neighboring counties that also participate in cloud seeding. First, when more hailstorms occurred in a county in the previous year, the odds ratio of participation in cloud seeding program significantly increases. This result suggests that regions experiencing frequent hailstorms naturally are more likely to adopt cloud seeding. The *Neighbor* variable is also statistically significant, indicating that if a county is surrounded by counties in the program, it is highly likely to also be in the program, and vice versa. These two results capture the characteristics of western counties in Kansas, which share similar geographical features and face challenges from extreme weather events.

Conversely, counties with a greater percentage of votes for the Republican Party have a higher likelihood of participation in the cloud seeding program. The coefficient for political ideology is much larger than the coefficient for hailstorm frequency. These results are consistent with Gould et al. (2024), indicating that while experiencing more extreme weather events, such as hailstorms, has a positive impact, political ideology strongly influences decision-making regarding weather-related mitigation policies. Finally, the results indicate that fiscal stress and loss ratios are not significantly correlated to participation in cloud seeding programs.

In the Logit model, a higher percentage of Republican votes increases the probability of participating in the cloud seeding program. Although Republicans are generally less favorable toward climate change policies (Chandler, 2009; Miao, 2019), the results from this analysis are consistent with Carman et al. (2022), who found that Republicans are more willing to engage in policies addressing extreme weather events rather than climate change. Additionally, Giordano et al. (2020) show that majority Republican communities experience policy changes following uncommon extreme weather events. With regard to hailstorms, the evaluation indicate that counties with a higher percentage of Republican votes are more likely to participate in cloud seeding programs to mitigate the impacts of extreme weather.

Table 16. Results of Logit model

Coefficient	(i)	(ii)	(iii)	(iv)
Fiscal stress	-0.277	-0.214	-0.389	-0.387
	(1.150)	(1.057)	(0.269)	(1.013)
Frequency	0.075*			
	(0.044)			
Magnitude		0.792		
		(1.334)		
Loss ratio (Hail)			0.269	
			(0.184)	
Loss ratio (Drought)				0.141
				(0.258)
Neighbor	-8.291***	-8.166***	-8.377***	-8.571***
	(1.761)	(1.686)	(1.749)	(1.747)
Republican	26.564***	25.483***	23.489**	23.163**
	(10.313)	(9.923)	(9.838)	(9.561)
Education	-27.921	-29.581	-0.207	-0.230
	(18.845)	(18.056)	(0.172)	(0.169)
Constant	-15.289*	-14.033*	-14.034	-12.621
	(8.764)	(8.334)	(8.703)	(8.434)
Observation	815	815	936	917

(2) Empirical results of policy termination

Table 17 presents the results of the Cox proportional hazards model. The dataset includes all samples—14 counties across 2003 to 2013—that adopted the cloud seeding program. This model evaluates the survival duration (i.e., the number of years until the program was terminated) using time-varying covariates. Additionally, counties that re-adopted the cloud seeding program and later terminated it are reintroduced into the analysis (Wang and Yao, 2023) Therefore, it is not necessary to exclude samples after their first opt-out from the program.

In column (i) of Table 17, the loss ratio due to hail significantly increases the probability (risk) of program termination, consistent with hypothesis 3. This result indicates that counties are more likely to terminate participation in the cloud seeding program if they continue to experienced a high hail-induced crop damage loss ratio despite cloud seeding. This variable reflects the perceived inefficacy of the program and the influence on the decision-making process for program termination.

A one percentage-point increase in the loss ratio due to hail raises the likelihood of a county government terminating the cloud seeding program by 16.1%. This result remains robust when controlling for other covariates, as shown in column (ii), where the likelihood of termination increases by 14.9% per percentage-point increase in the loss ratio.

Table 17. Results of Cox proportional hazard model

Hazard Ratio	(i)	(ii)	(iii)
Fiscal stress		0.301	0.527
		(0.339)	(0.376)
Loss ratio (Hail)	1.161**	1.149*	
	(0.083)	(0.089)	
Loss ratio (Drought)			0.524
			(0.289)
Neighbor		0.092**	0.054**
		(0.094)	(0.062)
Republican		1.040	0.292
		(3.656)	(0.796)
Education		4.589	56.489
		(18.312)	(225.820)
Observation	112	84	84

Surprisingly, among the counties participated in the cloud seeding program, the variable *Neighbor* significantly decrease the likelihood of termination. This finding indicates that county *i* is less likely to terminate participation if a neighboring county terminates. These results contradict the direction predicted by Hypothesis 4.

Diffusion theory suggests that local governments are influenced by their neighbors through processes of learning, competition, and adherence to norms and standards. In the case of Kansas, decisions by county officials to participate in cloud seeding are influenced by neighbors, though the exact source of this influence remains unclear.

Li (2017), for example, used a Cox proportional hazards model to investigate how policy diffusion influences the adoption of education policies by state governments. The author found that when more neighboring states adopt a policy, it delays adoption by the observed state, a phenomenon referred to as "inverse policy diffusion". Similarly, in this chapter, I found that a county is less likely to terminate the cloud seeding program as the percentage of neighboring counties terminating the program increases. Counties may choose to postpone termination to observe potential consequences and gather more information from their neighbors before making a decision.

In discussing the political aspects of policy termination, Weiss (1993) identifies three ways in which political ideology influences termination: political pressures, the provision of crucial evidence for termination within the political process, and the political messages carried by termination. None of these factors are evident in the case of the Kansas cloud seeding program, which does not support the hypothesis 2 However, it is notable that while counties with greater Republican voters are more likely to have participated, there is no evidence from this evaluation that Republican influences (or lack thereof) drove policy termination. The potential reason might be because Republicans dominate in most of Kansas counties, although the percentage of support changes within counties over time, the variation might not be reflected in the policy termination.

Finally, as shown in Table 17, there is no evidence to support Hypothesis 1, which posited that fiscal stress influences policy termination. Two possible explanations for this finding are as follows: First, the budget allocated to the cloud seeding program is relatively small compared to the overall county government budget, and cutting such a minor expenditure may not substantially alleviate fiscal stress. Second, most counties participating in the cloud seeding program prioritize disaster reduction and water resource preservation, making the program a strategic investment rather than a dispensable cost.

VII. Conclusion

Hailstorms cause significant damage in the US, and cloud seeding is considered a promising tool for reducing this risk. In Kansas, since 1972, the state government and county government authorities have collaborated on cloud seeding programs for nearly four decades. The state government has presented evidence that the program's cost-benefit ratio is 37. Despite the high estimated net benefit, many counties discontinued program participation and in 2016 the state government suspended the whole program.

In this paper I first used a Logit model to investigate the factors associated with county participation in cloud seeding programs. A summary of this portion of the evaluation is as follows. First, I found that counties experiencing more frequent hailstorms are more likely to participate in the cloud seeding program. Moreover, a county is more likely to participate in the program the higher is the percentage of border counties that participate in the program. Finally, counties with higher support rates for the Republican Party are more likely to participate in the cloud seeding program. In summary, counties participating in the cloud seeding program ten to have more hailstorms, strong Republican support, and have border counties that also participate in the cloud seeding program.

Focusing on those counties that participated in the cloud seeding program, I also examined factors that influence termination of the cloud seeding program. Specifically, I adopted a Cox proportional hazards model to examine the factors influencing termination decisions. I found that fiscal stress does not significantly influence termination decisions. This could be due to two reasons. First, the cost of the cloud seeding program constitutes only a small portion of the local government budget. Second, the program is highly subsidized by the state government. In addition, a higher loss ratio for hail in the previous period increases the likelihood of termination. This finding suggests that perceptions of program effectiveness based on recent past experience may influence the termination decision. Finally, I found the neighbors' decisions also influence termination decisions, which is consistent with the policy diffusion theory. In summary, this analysis offers new information regarding the policy termination process in the context of subnational government termination decisions.

There may be other potential factors influencing termination decisions that could not be included due to data constraints. First, cloud seeding programs can easily become "scapegoats" when undesired extreme weather events occur[63], such as droughts in Kansas, flooding in the UAE, and storms in California. This political pressure from public opinion might also influence policy termination. Second, the debate between strict termination and partial termination remains unresolved. While I did not find alternative policies specifically for cloud seeding programs aimed at hail suppression, crop insurance could potentially protect farmers from extreme weather damage, fulfilling a similar role to cloud seeding. This overlap might lead to the explicit termination of cloud seeding programs in favor of well-developed and highly subsidized crop insurance schemes. However, many aspects of policy termination remain uncertain, necessitating further research in the future.

[63] See the February 2014 newsletter from GMD1: "The upcoming 2014 season will see the program shrink to its smallest size since it began. Much of this decline is attributable to the program being a convenient scapegoat by the uninformed for the current prolonged drought." https://www.gmd1.org/2014_Feb_newsletter_final.pdf

REFERENCES

Abshaev, M. T., Abshaev, A. M., Malkarova, A. M., & Tsikanov, K. A. (2022). Hail suppression to protect crops in the North Caucasus. *Russian Meteorology and Hydrology, 47*(7), 487-498.

Allen, J. T., Giammanco, I. M., Kumjian, M. R., Punge, H. J., Zhang, Q., & Groenemeijer, P. (2020). Understanding hail in the Earth system. *Reviews of Geophysics, 58*(3), e2019RG000665. https://doi.org/10.1029/2019RG000665

Almheiri, K. B., Rustum, R., Wright, G., & Adeloye, A. J. (2021). Study of impact of cloud-seeding on intensity-duration-frequency (IDF) curves of Sharjah City, the United Arab Emirates. *Water, 13*(23), 1-15. https://doi.org/10.3390/w13233363

Auf der Maur, A., & Germann, U. (2021). A re-evaluation of the Swiss hail suppression experiment using permutation techniques shows enhancement of hail energies when seeding. *Atmosphere, 12*(12), 1623.

Beatty, T. K. M., Shimshack, J. P., & Volpe, R. J. (2019). Disaster preparedness and disaster response: Evidence from sales of emergency supplies before and after hurricanes. *Journal of the Association of Environmental and Resource Economists, 6*(4), 633-668.

Bennett, D. S. (1999). Parametric models, duration dependence, and time-varying data revisited. *American Journal of Political Science, 43*(1), 256-270.

Berry, F. S., & Berry, W. D. (1990). State lottery adoption as policy innovations: An event history analysis. *American Political Science Review, 84*(2), 395-415.

Berry, F. S., & Berry, W. D. (2014). Innovation and diffusion models in policy research. In P. A. Sabatier & C. Weible (Eds.), *Theories of the Policy Process* (3rd ed., pp. 307-359). Boulder, CO: Westview Press.

Boardman, A. E., Greenberg, D. H., Vining, A. R., & Weimer, D. L. (2018). The social discount rate. In *Cost-benefit analysis: Concepts and practice* (pp. 237-268). Cambridge: Cambridge University Press.

Box-Steffensmeier, J. M., & Jones, B. S. (1997). Time is of the essence: Event history models in political science. *American Journal of Political Science, 41*(4), 1414-1461.

Boyce, J. K. (2000). Let them eat risk? Wealth, rights and disaster vulnerability. *Disasters, 24*(3), 254-261.

Carman, J. P., Lacroix, K., Goldberg, M. H., Rosenthal, S., Gustafson, A., Howe, P., Marlon, J., & Leiserowitz, A. (2022). Measuring Americans' support for adapting to 'climate change' or 'extreme weather.' *Environmental Communication, 16*(5), 577-588. https://doi.org/10.1080/17524032.2022.2087709

Chandler, J. (2009). Trendy solutions: Why do states adopt sustainable energy portfolio standards? *Energy Policy, 37*(8), 3274-3281.

Changnon, S. A. (1971). Note on hailstone size distributions. *Journal of Applied Meteorology, 10*(2), 168-170.

Changnon, S. A., & Changnon, D. (2000). Long-term fluctuations in hail incidences in the United States. *Journal of Climate, 13*(4), 658-664.

Childs, S. J., Schumacher, R. S., & Demuth, J. L. (2020). Agricultural perspectives on hailstorm severity, vulnerability, and risk messaging in eastern Colorado. *Weather, Climate, and Society, 12*(4), 897-911.

Cross, H. Z., & Zuber, M. S. (1972). Prediction of flowering dates in maize based on different methods of estimating thermal units. *Agronomy Journal, 64*(3), 351-355.

DeFelice, T. P., Axisa, D., Bird, J. J., Hirst, C. A., Frew, E. W., Burger, R. P., Baumgardner, D., Botha, G., Havenga, H., Breed, D., Bornstein, S., Choate, C., Gomez-Faulk, C., & Rhodes, M. (2023). Modern and prospective technologies for weather modification activities: A first demonstration of integrating autonomous uncrewed aircraft systems. *Atmospheric Research, 290*, 106788. https://doi.org/10.1016/j.atmosres.2023.106788

DeFelice, T. P., Golden, J., Griffith, D., Woodley, W., Rosenfeld, D., Breed, D., Solak, M., & Boe, B. (2014). Extra area effects of cloud seeding—An updated assessment. *Atmospheric Research, 135-136*, 193-203.

DeLeon, P. (1987). Policy termination as a political phenomenon. In D. J. Palumbo (Ed.), *The politics of program evaluation* (pp. 209-233). Beverly Hills, CA: Sage.

Dessens, J., Sanchez, J. L., Berthet, C., Hermida, L., & Merino, A. (2016). Hail prevention by ground-based silver iodide generators: Results of historical and modern field projects. *Atmospheric Research, 170*, 98-111.

Dickie, M. (2017). Averting behavior methods. In P. Champ, K. Boyle, & T. Brown (Eds.), *A primer on nonmarket valuation* (2nd ed., pp. 293-346). Springer.

Dormady, N. C., Greenbaum, R. T., & Young, K. A. (2021). An experimental investigation of resilience decision-making in repeated disasters. *Environment Systems and Decisions, 41*(4), 556-576.

Eklund, D. L., Jawa, D. S., & Rajala, T. K. (1999). Evaluation of the Western Kansas Weather Modification Program. *Journal of Weather Modification, 31*, 91-101.

Fan, J., Zhang, Y., Wang, J., Jeong, J. H., Chen, X., Zhang, S., Lin, Y., Feng, Z., & Adams-Selin, R. (2022). Contrasting responses of hailstorms to anthropogenic climate change in different synoptic weather systems. *Earth's Future, 10*(7), e2022EF002768. https://doi.org/10.1029/2022EF002768

Federer, B., Waldvogel, A., Schmid, W., Schiesser, H. H., Hampel, F., Schweingruber, M., Stahel, W., Bader, J., Mezeix, J. F., & Doras, N. (1986). Main results of Grossversuch IV. *Journal of Applied Meteorology and Climatology, 25*(7), 917–957.

Ferry, M., & Bachtler, J. (2013). Reassessing the concept of policy termination: The case of regional policy in England. *Policy Studies, 34*(3), 255–273.

Foote, G. B., & Knight, C. A. (1979). Results of a randomized hail suppression experiment in Northern Colorado. Part I: Design and conduct of the experiment. *Journal of Applied Meteorology, 18*(12), 1526–1537.

Gavrilov, M. B., Markovic, S. B., Zorn, M., Komac, B., Lukic, T., Milosevic, M., & Janicevic, S. (2013). Is hail suppression useful in Serbia? General review and new results. *Acta Geographica Slovenica, 53*(1), 165–179.

Geva-May, I. (2001). When the motto is "till death do us part": The conceptualization and the craft of termination in the public policy cycle. *International Journal of Public Administration, 24*(3), 263–288.

Geva-May, I. (2004). Riding the wave of opportunity: Termination in public policy. *Journal of Public Administration Research and Theory, 14*(3), 309–333. https://doi.org/10.1093/jopart/muh020

Gould, R. K., Shrum, T. R., Harrington, D. R., & Iglesias, V. (2024). Experience with extreme weather events increases willingness-to-pay for climate mitigation policy. *Global Environmental Change, 85,* 102795.

Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics, 2*(2), 111-120.

Hausken, K. (2021). The precautionary principle as multi-period games where players have different thresholds for acceptable uncertainty. *Reliability Engineering and System Safety, 206,* 107224.

Hogwood, B. W., & Peters, G. B. (1982). The dynamics of policy change: Policy succession. *Policy Sciences, 14*(3), 225-245.

Hwang, S. J. (2021). An exploration of the diffusion of policy termination: The repeal of prevailing wage laws by US state governments. *Policy Studies, 42*(2), 117-131.

IPCC**.** (2012). Field, C. B., Barros, V., Stocker, T. F., Qin, D., Dokken, D. J., Ebi, K. L., Mastrandrea, M. D., Mach, K. J., Plattner, G.-K., Allen, S. K., Tignor, M., & Midgley, P. M. (Eds.). *Managing the risks of extreme events and disasters to advance climate change adaptation: A special report of working groups I and II of the Intergovernmental Panel on Climate Change (IPCC)*. Cambridge University Press.

IPCC. (2014). Summary for policymakers. In C. B. Field, V. R. Barros, D. J. Dokken, K. J. Mach, M. D. Mastrandrea, T. E. Bilir, M. Chatterjee, K. L. Ebi, Y. O. Estrada, R. C. Genova, B. Girma, E. S. Kissel, A. N. Levy, S. MacCracken, P. R. Mastrandrea, & L. L. White (Eds.), *Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. Contribution of working group II to the fifth assessment report of the Intergovernmental Panel on Climate Change* (pp. 1-32). Cambridge University Press.

Jiang, F., Meng, S., Halim, N., & Mozumder, P. (2022). Departure timing preference during extreme weather events: Evidence from hurricane evacuation behavior. *Transportation Research Record.* https://doi.org/10.1177/03611981211066901

Jones, B. S., & Baranton, R. P. (2005). Beyond logit and probit: Cox duration models of single, repeating, and competing events for state policy adoption. *State Politics & Policy Quarterly, 5*(4), 420-443.

Kailiponi, P. (2010). Analyzing evacuation decisions using multi-attribute utility theory. *International Conference on Evacuation Modeling and Journal of Environmental Economics.* https://www.semanticscholar.org/paper/Analyzing-evacuation-decisions-using-utility-theory-Kailiponi/ea12048660f6ab5998fd0619dfb4c711b56c030c

Kasdin, S., & McCann, A. (2021). What drives program terminations for the federal government? *Public Budgeting & Finance, 42*(1), 28-44.

Kim, M. J. (2021). Air pollution, health, and avoidance behavior: Evidence from South Korea. *Environmental and Resource Economics, 79*(1), 63-91. https://doi.org/10.1007/s10640-021-00553-1

Kirkpatrick, S. E., Lester, J. P., & Peterson, M. R. (1999). The policy termination process. *Review of Policy Research, 16*(1), 209-238.

Knowles, S., & Skidmore, M. (2021). Cloud seeding and crop yields: Evaluation of the North Dakota Cloud Modification Project. *Weather, Climate, and Society, 13*(4), 885-898.

Kostecki, D. F. (1977). *Weather modification activities in Kansas 1972-1977.* Bulletin 22, Kansas Water Resources Board.

Krause, R. M., Yi, H., & Feiock, R. C. (2016). Applying policy termination theory to the abandonment of climate protection initiatives by U.S. local governments. *The Policy Studies Journal*, *44*(2), 176-195.

Miami-Dade Transportation Planning Organization. (2018). *Factors affecting transit ridership in Miami-Dade County.* https://www.miamidadetpo.org/library/studies/factors-affecting-transit-ridership-in-miami-dade-county-final-report-2018-11.pdf

McMaster, G. S., & Smika, D. E. (1988). Estimation and evaluation of winter wheat phenology in the central Great Plains. *Agricultural and Forest Meteorology, 43*, 1-18.

Metzger, S. K., & Jones, B. T. (2022). Getting time right: Using Cox models and probabilities to interpret binary panel data. *Political Analysis, 30*(2), 151-166.

Miao, Q. (2019). What affects government planning for climate change adaptation: Evidence from the U.S. states. *Environmental Policy and Governance, 29*(5), 376-394.

Moretti, E., & Neidell, M. (2011). Pollution, health, and avoidance behavior: Evidence from the ports of Los Angeles. *Journal of Human Resources, 46*, 154-175.

National Center for Environmental Information. (2009). *State Climate Extremes Committee: Proposed standards for the collection, storage, and measurement of hailstones.* Retrieved from https://www.ncdc.noaa.gov/monitoring-content/extremes/scec/reports/SCEC-Hail-Guide.pdf

National Science and Technology Center for Disaster Reduction. (2011). *Disaster survey and analysis of Morakot typhoon* (Chinese version only). NCDR.

Neidell, M. (2009). Information, avoidance behavior, and health: The effects of ozone on asthma hospitalizations. *Journal of Human Resources*, *44*, 450-478.

NOAA National Centers for Environmental Information (NCEI). (2022). *U.S. billion-dollar weather and climate disasters*. https://www.ncei.noaa.gov/access/billions/ https://doi.org/10.25921/stkw-7w73

Pan, Y., Yan, C., & Archer, C. L. (2018). Precipitation reduction during Hurricane Harvey with simulated offshore wind farms. *Environmental Research Letters*, *13*, 084007.

Pesaran, M., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, *142*, 50-93.

Pirani, F. J., Najafi, M. R., Joe, P., Brimelow, J., McBean, G., Rahimian, M., Stewart, R., & Kovacs, P. (2023). A ten-year statistical radar analysis of an operational hail suppression program in Alberta. *Atmospheric Research*, *295*, 107035.

Púčik, T., Castellano, C., Groenemeijer, P., & Kuhne, T. (2019). Large hail incidence and its economic and societal impacts across Europe. *Monthly Weather Review*, *147*, 3901-3916.

Rhee, J. W., & Jang, Y. J. (2022). Determinants of termination of anti-dumping measures: The case of Korea. *East Asian Economic Review*, *26*(2), 95-117.

Rivera, J. A., F. Otero, E. N. Tamayo, and M. Silva (2020) Sixty years of hail suppression activities in Mendoza, Argentina: Uncertainties, gaps in knowledge and future perspectives. Frontiers in Environmental Science, 8:45. doi: 10.3389/fenvs.2020.00045.

Rymbai H, Deshmukh N. A., Verma V. K., Talang H. D., Devi MB, Jha AK (2019) Impact assessment of hailstorm on khasi mandarin and other horticultural crops in Umiam, Meghalaya. Ind J Hill Farm 56-61.

Rabassa, M. J., Grand, M. C., & Garcia-Witulski, C. M. (2021). Heat warnings and avoidance behavior: Evidence from a bike-sharing system. *Environmental Economics and Policy Studies*, *23*, 1-28.

Rivera, J. A., Otero, F., Tamayo, E. N., & Silva, M. (2020). Sixty years of hail suppression activities in Mendoza, Argentina: Uncertainties, gaps in knowledge and future perspectives. *Frontiers in Environmental Science*, *8*. https://doi.org/10.3389/fenvs.2020.00045

Rodo, X., & Comin, F. A. (2003). Global climate current research and uncertainties in the climate system. In F. A. Comin (Ed.), *Springer Environmental Management Series* (pp. 189). Springer.

Rogna, M., Schamel, G., & Weissensteiner, A. (2021). The apple producers’ choice between hail insurance and anti-hail nets. *Agricultural Finance Review*, *82*, 20-48.

Rogna, M., Schamel, G., & Weissensteiner, A. (2022). Modelling the switch from hail insurance to anti-hail nets. *The Australian Journal of Agricultural and Resource Economics*. https://doi.org/10.1111/1467-8489.12499

Rymbai, H., Deshmukh, N. A., Verma, V. K., Talang, H. D., Devi, M. B., & Jha, A. K. (2019). Impact assessment of hailstorm on Khasi mandarin and other horticultural crops in Umiam, Meghalaya. *Indian Journal of Hill Farming, 32*(2), 56-61.

Sarafidis, V., & Weber, N. (2015). A partially heterogeneous framework for analyzing panel data. *Oxford Bulletin of Economics and Statistics, 77*, 274-296.

Sheldon, T. L., & Sankaran, C. (2019). Averting behavior among Singaporeans during Indonesian forest fires. *Environmental and Resource Economics, 74*, 159-180.

Shipan, C. R., & Volden, C. (2008). The mechanisms of policy diffusion. *American Journal of Political Science, 52*(4), 840-857.

Simeonov, P. (1996). An overview of crop hail damage and evaluation of hail suppression efficiency in Bulgaria. *Journal of Applied Meteorology, 35*, 1574-1581.

Sophocleous, M. (2005). Groundwater recharge and sustainability in the High Plains aquifer in Kansas, USA. *Hydrogeology Journal, 13*, 351-365.

Spiridonov, V., Karacostas, T., Bampzelis, D., & Pytharoulis, I. (2015). Numerical simulation of airborne cloud seeding over Greece, using a convective cloud model. *Asia-Pacific Journal of Atmospheric Sciences, 51*, 11-27.

Thompson, C. M., & Dezzani, R. J. (2021). Examining relationships between traditional vulnerability data proxies and hurricane risk perception indicators. *Journal of Risk Research*, *24*(8), 913-930.

Tuftedal, M. E., Delene, D. J., & Detwiler, A. (2022). Precipitation evaluation of the North Dakota Cloud Modification Project (NDCMP) using rain gauge observations. *Atmospheric Research, 269*. https://doi.org/10.1016/j.atmosres.2021.105996

Wang, C., & Liu, I. S. (2024). Unraveling the politics-science nexus: Diverse strategies in US states' termination of mask policies. *Policy Studies*. https://doi.org/10.1080/01442872.2024.2303356

Wang, W., Yao, Z., Guo, J., Tan, C., Jia, S., Zhao, W., Zhang, P., & Gao, L. (2019). The extra-area effect in 71 cloud seeding operations during winters of 2008–2014 over Jiangxi Province, East China. *Journal of Meteorological Research, 33*, 528-539. https://doi.org/10.1007/s13351-019-8122-1

Wenzelburger, G., & Hartmann, K. (2022). Policy formation, termination, and the multiple streams framework: The case of introducing and abolishing automated university admission in France. *Policy Studies, 43*(5), 1075-1095.

Whitehead, J. C. (2005). Environmental risk and averting behavior: Predictive validity of jointly estimated revealed and stated behavior data. *Environmental and Resource Economics, 32*, 301-316.

World Bank. (2005). *Natural disaster hotspots: A global risk analysis*. https://openknowledge.worldbank.org/handle/10986/7376

Yoo, C., Na, W., Cho, E., Chang, K. H., Yum, S. S., & Jung, W. (2022). Evaluation of cloud seeding on the securement of additional water resources in the Boryeong Dam

Basin, Korea. *Journal of Hydrology, 613*.
https://doi.org/10.1016/j.jhydrol.2022.128359

APPENDIX

Table A1 Avoidance behavior _Miami Dade County Metrobus system (time trend)

Specification	(5a)	(5b)	(5c)	(5d)
$\ln(\text{busride}_{t-1})$	0.392***	0.394***	0.398***	0.394***
$\ln(\text{busride}_{t-2})$	-0.393***	-0.393***	-0.393***	-0.395***
Awind	-0.006**	-0.007***	-0.007***	-0.007***
rain	-0.087***	-0.089***	-0.088***	-0.088***
Alarm	-0.317***			
Alarm_{t-1}		-0285***		-0.201**
Alarm_{t-2}			-0.260***	-0.138*
dow	-0.012**	-0.012**	0.011**	0.012***
moy	-0.008***	-0.008***	-0.008***	-0.008***
_cons	17.175***	17.174***	14.616***	14.632***
R-squared	0.311	0.309	0.308	0.310

Table A2 Avoidance behavior _ Miami Dade County Metrorail system (time trend)

Specification	(5a)	(5b)	(5c)	(5d)
$\ln(\mathbf{metroride}_{t-1})$	0.539***	0.541***	0.544***	0.541***
$\ln(\mathbf{metroride}_{t-2})$	-0.436***	-0.435***	-0.435***	-0.436***
Awind	-0.006	-0.006*	-0.007*	-0.006*
rain	-0.064***	-0.067***	-0.066***	-0.066***
Alarm	-0.305***			
$\mathbf{Alarm}_{t-1}$		-0.238***		-0.169*
$\mathbf{Alarm}_{t-2}$			-0.216***	-0.113
dow	-0.017**	-0.017**	-0.018**	-0.018**
ym	-0.004***	-0.004***	-0.004***	-0.004***
_cons	12.725***	12.718***	12.689***	11.047***
R-squared	0.307	0.304	0.304	0.305

Note: Wind doesn't affect the passenger rides of rail system significantly. The reason might be because rail system provides cover for users.

Table A3 Avoidance behavior _ Miami Dade County Metromover system (time trend)

Specification	**(5a)**	**(5b)**	**(5c)**	**(5d)**
ln(moverride$_{t-1}$)	0.319***	0.320***	0.321***	0.320***
ln(moverride$_{t-2}$)	-0.029	-0.029	-0.029	-0.030
Awind	-0.006	-0.007	-0.007*	-0.007
rain	-0.066**	-0.067***	-0.067***	-0.067***
Alarm	-0.231**			
Alarm$_{t-1}$		-0.198**		-0.150
Alarm$_{t-2}$			-0.166*	-0.076
dow	0.015**	0.015**	0.015**	0.015**
ym	-0.003***	-0.003***	-0.003***	-0.003***
_cons	8.871***	8.859***	8.842***	8.850***
R-squared	0.126	0.125	0.124	0.125

Table B1. Crop damage indemnity (dollars per insured acre)

Variable	Total			Kansas			West Kansas		
	hail	drought	flooding	hail	drought	flooding	hail	drought	flooding
Seed	0.47 (0.56)	-1.68 (3.21)	1.28* (0.72)	0.33 (0.58)	-3.73 (3.27)	1.54* (0.79)	0.61 (0.73)	1.38 (2.61)	1.11 (0.79)
UWseed	0.09 (0.80)	6.05 (4.56)	0.17 (1.03)	0.001 (0.82)	5.07 (4.61)	0.24 (1.11)	0.25 (1.00)	6.37* (3.59)	0.241 (1.08)
Wet	0.15 (0.13)	-3.72*** (0.74)	2.26*** (0.16)	0.26* (0.16)	-3.37*** (0.93)	2.52*** (0.22)	0.33 (0.26)	-2.30** (0.95)	1.20*** (0.29)
Dry	-0.99*** (0.19)	12.31*** (1.10)	0.80*** (0.25)	-0.79*** (0.23)	16.24*** (1.32)	0.80** (0.32)	-0.98*** (0.37)	8.71*** (1.34)	0.45 (0.41)
GDD	0.0001 (0.0003)	-0.001 (0.001)	-0.001* (0.0003)	0.0001 (0.0002)	-0.002 (0.002)	-0.001** (0.0004)	-0.0001 (0.001)	-0.004* (0.002)	0.0004 (0.001)
SDD	0.001 (0.001)	0.015** (0.006)	0.001 (0.001)	0.001 (0.001)	0.022*** (0.007)	0.003 (0.002)	0.003 (0.002)	0.025*** (0.008)	-0.001 (0.002)
County Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square									
within	0.125	0.476	0.310	0.114	0.547	0.329	0.190	0.563	0.116
between	0.063	0.001	0.030	0.002	0.073	0.081	0.094	0.142	0.015
Overall	0.077	0.422	0.230	0.081	0.510	0.231	0.134	0.508	0.100

*:10%, **:5%, ***:1% statistic significant.

Table B2. Cloud seeding effects (Total sample)

Variable	Weather variables			Crop loss ratio			Crop productivity		
	frequency	magnitude	rainfall	hail	drought	flooding	Wheat	Corn	Sorghum
Seed	-0.28 (1.16)	-0.05 (0.04)	0.06 (0.05)	0.27 (0.27)	0.16 (0.13)	0.53*** (0.16)	-0.70 (1.51)	16.22*** (3.93)	-3.44 (2.50)
UWseed	2.78* (1.63)	0.10* (0.06)	-0.09 (0.07)	-0.10 (0.38)	0.22 (0.19)	0.11 (0.24)	-2.95 (2.21)	4.41 (5.63)	-11.02*** (3.52)
Wet	0.34 (0.26)	-0.001 (0.009)	0.29*** (0.01)	0.15** (0.06)	0.09*** (0.03)	0.23*** (0.04)	-1.13*** (0.37)	1.24 (0.99)	3.01*** (0.67)
Dry	-1.67*** (0.40)	-0.01 (0.02)	-0.13*** (0.02)	0.35*** (0.10)	0.58*** (0.05)	0.20*** (0.06)	-3.53*** (0.52)	-7.38*** (1.31)	-9.98*** (0.91)
GDD	0.0003 (0.001)	0.0001 (0.0001)	0.0001*** (0.00002)	0.0002 (0.0001)	0.00003 (0.0001)	-0.0001 (0.0001)	-0.001 (0.001)	0.01*** (0.002)	0.01*** (0.001)
SDD	0.001 (0.002)	-0.0001 (0.0001)	-0.001*** (0.0001)	-0.001 (0.001)	0.0001 (0.0003)	0.001* (0.0003)	0.003 (0.003)	-0.04*** (0.007)	-0.03*** (0.005)
County Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square									
within	0.164	0.103	0.599	0.130	0.454	0.158	0.390	0.457	0.651
between	0.0001	0.044	0.493	0.015	0.076	0.011	0.093	0.003	0.123
Overall	0.095	0.081	0.101	0.099	0.418	0.132	0.306	0.137	0.477
Observations	2,259	2,259	2,319	2,196	2,154	2,128	1,762	1,665	1,468

*:10%, **:5%, ***:1% statistic significant.

C. Farmers Production Model

Link to the model section, the government officers can levy tax from the residents. And based on Hettich and Winer (1984, 1988), the taxable activity can be derived from the production functions.

The cloud seeding program serves as a tool to mitigate hail damage, with the expectation that target areas experience increased agricultural productivity. However, the downwind effect may result in unintended impacts from the cloud seeding program. To offer a clearer assessment of these potential effects, consider the damage control model, as proposed by Lichtenberg and Zilberman (1986). In this approach, damage control agents, such as pest control and theft prevention, play a crucial role in preserving crop production and profitability.

Building on the work of Knowles and Skidmore (2021), who applied the damage control framework to the evaluation of cloud seeding programs as damage control agents for wheat and barley crops in North Dakota. Of direct relevance, Trilnick and Zilberman (2021) developed a structural model based on the damage control approach, which introduced microclimate engineering and sunlight reflection as damage control agents for pistachio yields in California.

In equation (1), $Y_{it}(Z,W)$ represents the potential output function under weather conditions W, encompassing factors such as temperature, moisture, hail, etc. Z is a vector of production inputs, including fresh water, fertilizer, and labor, etc. $Y_{it}^{0}(Z)$ denotes the minimum crop output regardless of weather conditions, which is interpreted as the crop resiliency. For instance, it may account for a portion of the crops surviving after hail damage, and farmers might implement post-hail remedies to expedite the recovery of crops from damage. $G_{it}(W(c_{it}))$ is the damage or loss function, where $G_{it}(W\ (c_{it})) \in [0,1]$, and c_{it} indicates whether county *i* participated in cloud seeding program, the damage control of hail, in year *t* or not.

$$Y_{it}(Z,W) = Y_{it}^{0}(Z) + Y_{it}^{1}(Z)\{1 - [G_{it}(W_i(c_{it})]\} \tag{A1}$$

With this production function, farmers collectively in county i address the profit maximization problem outlined in equation (2), where p_y, p_z, and p_c represent the prices of outputs, inputs, and participation in the cloud seeding program, respectively. For simplicity, here after denote $Y_{it}^0(Z)$ as equal to zero.

$$\max_{c_{it}} \quad \pi_{it} = p_y\{Y_{it}^1(Z)[1 - G_{it}(W_i(c_{it}))] - p_z Z - p_c c_{it} \tag{A2}$$

Assuming that farmers do not adjust inputs, Z, in conjunction with the decision of whether or not to participate in the cloud seeding program, the marginal effect of cloud seeding participation on profit is shown in equation (3).

$$\frac{d\pi_{it}}{dc_{it}} = p_y Y_{it}^1(Z)(-\frac{\partial G_{it}}{\partial W_{it}}\frac{\partial W_{it}(c_{it})}{\partial c_{it}}) - p_c \tag{A3}$$

From equation (3), the price and production are both positive terms. In general, weather conditions have a positive correlation with damage ($\frac{\partial G(W(.))}{\partial W}$>0). For instance, when more hailstorms occur in a year, there is a higher probability of crop damage. Moreover, as predicted by the beneficial competitiveness hypothesis (see section II), if the cloud seeding program effectively modifies adverse weather impacts such as reducing hailstorm frequency and magnitude, then $\frac{\partial W(c_{it})}{\partial c_{it}}$<0.

The damage abatement model should also account for spatial spillovers. For instance, Schneider et al. (2021) demonstrated that the timing of pest population control by one farmer can influence the efficacy of neighboring farmers' damage abatement inputs. In this study, I incorporate spatial spillovers into the model, where upwind county *j*'s decision regarding participation in the cloud seeding program influences county *i*'s weather, such as less rainfall or hailstorms. The revised maximization problem is illustrated in equation (4), and the marginal effect of cloud seeding participation on profit is shown in equation (5).

$$\max_{c_{it}} \quad \pi_{it} = p_y\{Y_{it}^1(Z)[1 - G_{it}\big(W_i(c_{it}, c_{jt})\big)] - p_z Z - p_c c_{it} \tag{A4}$$

$$\frac{d\pi_{it}}{dc_{it}} = p_y Y_{it}^1(Z)\left(-\frac{\partial G_{it}}{\partial W_{it}}\frac{\partial W_{it}(c_{it}, c_{jt})}{\partial c_{it}}\right) - p_c \tag{A5}$$

In the damage control model, the damage control agent may not directly enhance crop production; in some cases, it might even lead to a reduction in crop production (Lichtenberg and Zilberman, 1986). For instance, pesticides may not directly improve crop yield but can reduce pests, resulting in better plant growth. However, excessive pesticide application can harm crop plants. Similarly, if cloud seeding is effective and spillover effect is not considered, then $\frac{\partial W(c_{it})}{\partial c_{it}}$<0. However, if spillover effects are taken into consideration, the sign $\frac{\partial W_{it}(c_{it}, c_{jt})}{\partial c_{it}}$ is unknown; it could be either positive or negative. Based on this model, in the following section, the efficacy of cloud seeding and potential spillover effects are tested.

Table D1. Net Benefit and Net Present Value of Counties Participating in the Cloud Seeding Program (2002–2016)

County	Number of years participating in program during 2002-2016	Net benefit (2002-2016) (real 2002 dollars)	Net Present Value	
			Discount rate 3.1%	Discount rate 3.9%
Finney	10	22,385,099	19,300,000	18,600,000
Gove	2	1,459,277	1,065,190	984,491
Grant	8	11,625,797	9,338,420	8,858,088
Gray	10	19,057,089	15,300,000	14,500,000
Greeley	6	11,344,974	8,027,018	7,364,672
Hamilton	11	10,271,209	8,280,079	7,855,697
Haskell	8	36,540,874	29,600,000	28,200,000
Kearny	13	12,153,677	10,000,000	9,580,517
Lane	14	-6,337,185	-5,135,528	-4,883,257
Scott	14	9,101,877	8,026,396	7,793,650
Stanton	6	15,862,281	12,500,000	11,800,000
Stevens	2	7,954,878	6,330,899	5,975,491
Wallace	2	1,976,468	1,597,694	1,515,924
Wichita	11	17,683,923	14,700,000	14,000,000

*Price is average price of each month of grain crops. The production gain and loss are based on the estimation of Table 3.

Table D2. Net Present Value of Cloud Seeding Program in Kansas

	Net present value (2002-2016)	
Real Discount Rates	3.1%	3.9%
NPV (participating)	-28,031,183	-29,149,102
NPV (non-participating)	39,009,128	41,324,710
Overall	10,977,945	12,175,608