(2024) 54, 259–282

The Review of Regional Studies

The Official Journal of the Southern Regional Science Association

Tropical Cyclone Day-off Orders, Warnings, and Avoidance Behavior*

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Abstract: Tropical cyclones, also known as hurricanes and typhoons, cause fatalities and significant economic losses every year. Alarms, warnings, and mandatory orders from governments play a crucial role in helping people avoid the harmful impacts caused by natural disasters. In Taiwan, the typhoon day-off order is a policy that mandates a day off from work and school for residents to stay put or evacuate from hazardous zones. However, implementing this order may result in economic losses when forecasts are incorrect, and storms change paths. Alternatively, the government could provide information and warnings about tropical cyclones, enabling residents to make avoidance decisions based on their current temporal and spatial circumstances. This article uses aggregate transportation time-series data to capture avoidance behavior in response to tropical cyclones. Results show that people respond to both alarms/warnings and government-mandated orders in differing degrees. This article further examines avoidance behaviors in response to similar intensities of tropical cyclones with and without mandatory orders, showing similar patterns and magnitudes of avoidance behavior in both regimes. Findings help inform policy decisions about the use of mandates and the issuance of critical information and warnings.

Keywords: Avoidance behavior, Disaster warning, Tropical cyclones, Public transportation
JEL Codes: Q54, Q58

1. 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

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

ISSN 1553-0892, 0048-49X (online)
www.srsa.org/rrs

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 damage(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 one 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, we 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 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(Field et al., 2012). False risk perceptions in turn lead to gaps between hazardous events and the severity of the consequences, resulting in insufficient averting behaviorThompson 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(Dormady 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 our 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 article, we 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, our 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. We therefore examine transportation usage patterns in different regions with different disaster policies to learn more about disaster aversion behavior in two policy regimes. We 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. First, to the best of our knowledge, this article is the first to discuss how people respond to government-mandated day-off orders. Our 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, we also use aggregate transportation data to analyze responses to information without government mandates. Third, we provide case studies from two regions and compare responses of citizens under mandatory orders versus information-only schemes.

The article proceeds as follows. Section 2 provides background on Taiwan and Miami's cyclone policies, section 3 describes the data, section 4 describes the empirical approach, section 5 presents the results, and discussions with conclusions are presented in section 6.

2. BACKGROUND

Taiwan is a hot spot for 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 Taiwan 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(National Science and Technology Center for Disaster Reduction, 2011).

On average, four typhoons make landfall in Taiwan every year with strong winds as the main cause of damage. However, even though some typhoons pass by Taiwan without a direct impact, they may come with a southwesterly flow.[3] Sometimes several typhoons

[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.

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

pass by together and cause the Fujiwara effect. In these 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 damage, national and subnational governments provide instructions and information to the public, which 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 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.

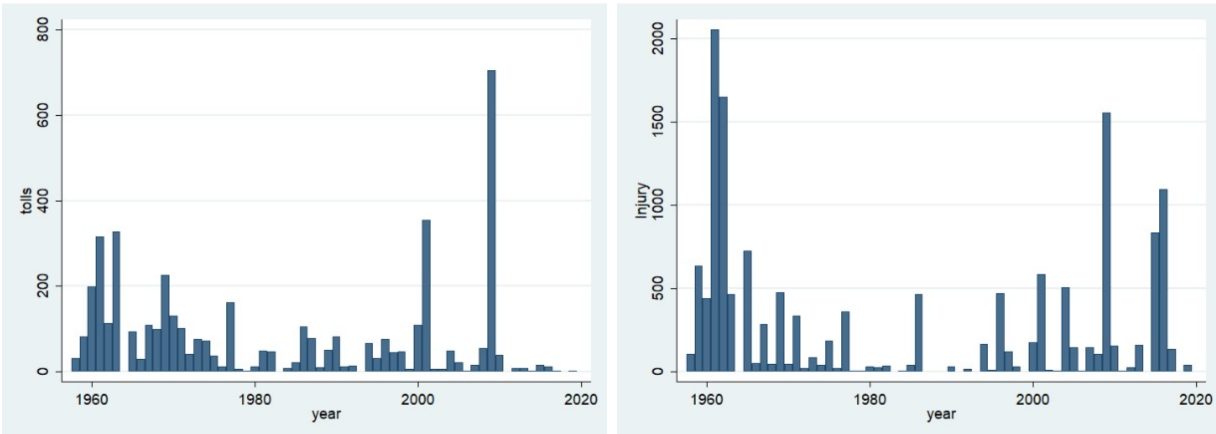
The decrease in death was coincident with the implementation of the typhoon day-off policy in the 1980s. In Taiwan, government officials announce a "typhoon day-off" when a typhoon or other severe weather events occur. When officials announce the orders, the stock market is closed, and all governmental 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

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

Figure 1: Tolls and Injuries during Tropical Cyclones in Taiwan (1958-2019)



Notes: The left figure shows total tolls, and the right figure shows injuries during tropical cyclones in Taiwan from 1958 to 2019.

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 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. We can therefore treat a typhoon day-off order 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, a majority of people trust the

Central Weather Bureau and the day-off decisions made by local governments, 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.[5]

We hypothesize that mandatory government orders have a larger avoidance effect than warnings during tropical cyclones. In other words, we 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, we 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, we expect a significant decrease in public transportation usage. During a tropical cyclone, a decline in public transportation usage may indicate that aversion strategies are being taken by residents within the cyclone-affected areas.

3. DATA

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

3.1. 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,

[5] The government announces 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 announces 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.

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 the Taipei Rapid Transit Corporation and the Kaohsiung Rapid Transit Corporation.[6] 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 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, the transportation data come from the Department of Transportation and Public Works (DTPW), including 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 component 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.[7] 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. We dropped those three data points from our dataset.[8]

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

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

[8]The Metrobus and Metrorail service were officially recorded as closed on October 6, 2016, but in our dataset,

3.2. Weather data

Taiwan's typhoon data come from the Typhoon Database,[9] which provides information on typhoon scale, routes, event date, maximum wind speed near the typhoon center, and typhoon warnings. 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.[10] 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, we collect daily weather data from 2009 to 2019. Weather data come from the Central Weather Bureau Observation Data Inquiry System.[11] On average, each city has at least one weather station and several automatic weather stations. We use data from traditional weather stations for each city because the data from automatic weather stations do not cover our research period.

Typhoon routes are another 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 local government officials will not issue a day-off order.[12] The routes data is also from the typhoon database.

The weather information in Miami includes tropical cyclone data and historical weather data. We 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/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

15,472 and 2,764 rides on Metrobus and Metrorail were recorded, respectively.

[9]Typhoon Database: https://rdc28.cwb.gov.tw/TDB/.

[10]Historical day-off order: https://www.dgpa.gov.tw/en/index?mid=138.

[11]Central Weather Bureau Observation Data Inquire System: https://e-service.cwb.gov.tw/HistoryDataQuery/.

[12]Ten different tracks in the typhoon database, see: https://rdc28.cwa.gov.tw/TDB/public/basic_query/.

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

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

the NHC and CPHC.[15] For studying avoidance behavior in Miami-Dade County, we first determine how many tropical cyclones affected the target areas. To do this, we 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 affected Miami-Dade County over the period of analysis.

We 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.

3.3. Hurricanes and typhoons data

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. In the data, half of all 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

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 our research, when we compare two different places, we examine the behavior when people receive day-off orders and hurricane alarms for tropical cyclones of similar magnitudes.

[15] Hurricane and tropical storm watch/warning breakpoints map: https://www.nhc.noaa.gov/breakpoints/.
[16] See: https://www.ncdc.noaa.gov/cdo-web/datatools/selectlocation.

Table 2: Magnitudes of Tropical Cyclones

Taiwan Scale	Wind Speed (km/hour)	Miami-Dade County 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 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-Dade 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 (mm)	1,826	4.83	12.5	0.0	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-Dade wind speed (m/s)	1,824	3.53	1.4	0.9	17.2

4. 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.

4.1. Conceptual model

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

$$\text{Safety} = f\,(\text{tropical cyclone} \times \text{avoid}, V)$$

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.

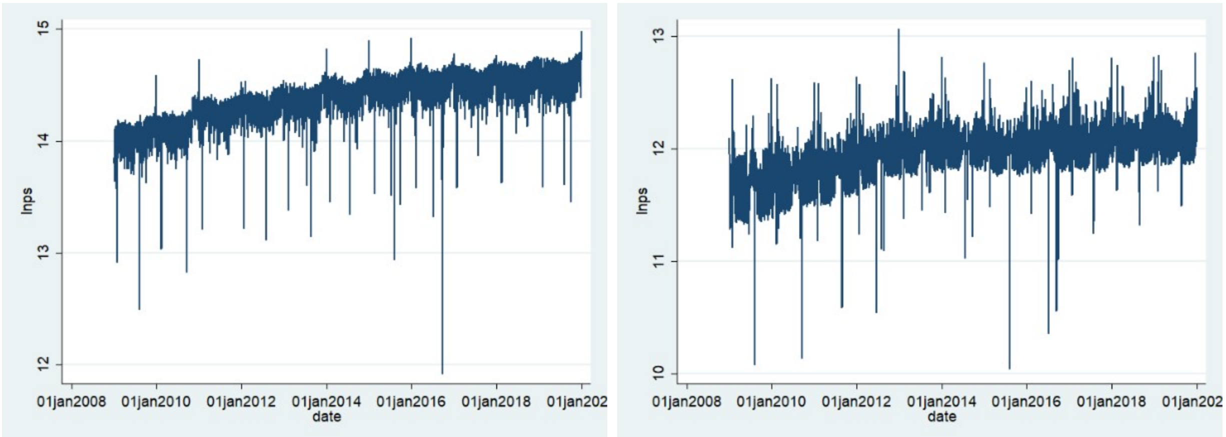
Suppose that social and environmental investments can enhance human safety. In the production function, the frequency and magnitude of hazardous events are negatively related to safety. For example, Category 5 hurricanes might reduce the life expectancy of residents in affected areas. However, avoidance 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.

4.2. 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 our main data, and Figure 2 presents time trends in the data.[17] 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. We control time 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.

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

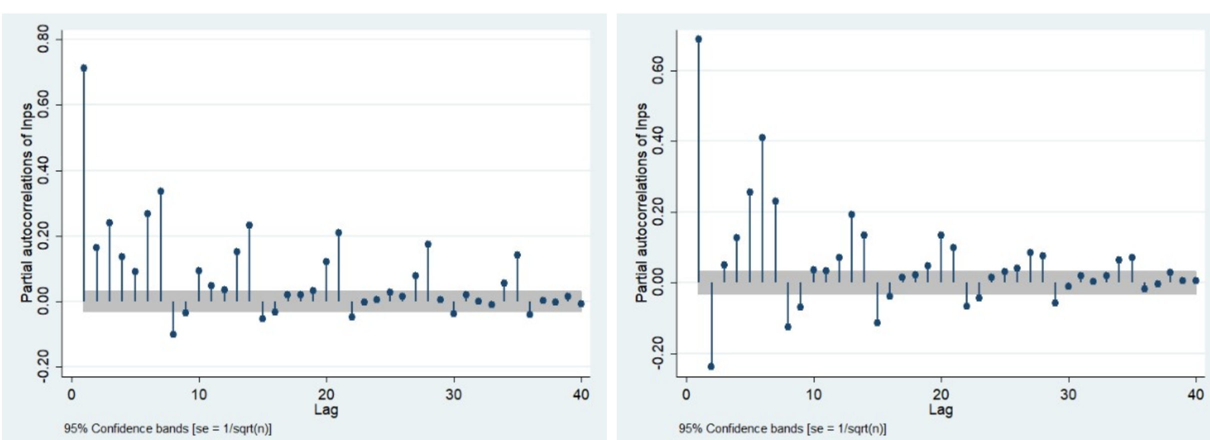
Figure 2: Passenger Trips for Metro Systems



*Notes:*The left figure shows the time trend of passenger trips for the Taipei Metro system, while the right figure shows the time trend for the Kaohsiung Metro system.

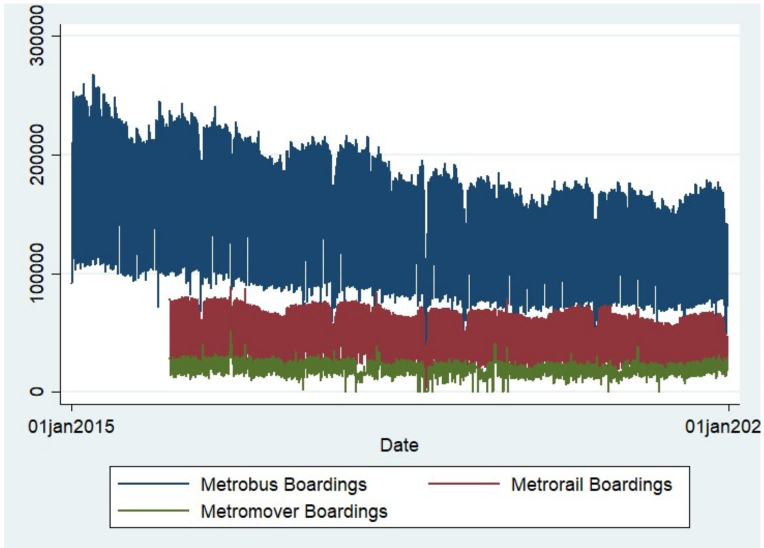
When using high-frequency time-series data, there may also be serial correlation issues. We therefore conduct a Durbin-Watson test, revealing that serial correlation problems are present. Figure 3 shows the partial autocorrelations, and the autocorrelations exhibit seasonality. From the graph, seven periods (days) form a cycle and show that the metro system appears to have a weekly pattern. We 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.

Figure 3: Partial Autocorrelations of Passenger Trips



*Notes:*The left figure and the right figure show the partial autocorrelations of Taipei Metro passenger trips and Kaohsiung Metro passenger trips, respectively.

Figure 4: Passenger Rides of Three Public Transportation Systems in Miami-Dade County



For the Miami Dade-county case, unlike Taiwan, Figure 4 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.

4.3. Empirical strategy

In the empirical analysis, we evaluate responsiveness of people to typhoon alarms. After testing and modifying the time series data as described in section 4.2, we employ ordinary least squares regression analysis in this study, as illustrated in Equation (1).

$$\begin{aligned} log(PS_t) &= \alpha_1 \log(PS_{t-1}) + \alpha_2 \log(PS_{t-2}) + \beta_1 doff_t \\ &+\gamma_1 wind_{t-1} + \gamma_2 route_{t-1} + \gamma_3 wind_{t-1} \times route_{t-1} + \phi_1 rain_{t-1} \\ &+\rho_1 nholiday_t + \rho_2 DOW + \rho_3 MOY + \epsilon_t \end{aligned} \tag{1}$$

where PS_t is the total count of daily passengers in the Kaohsiung metro system from 2009 to 2019. Use of the log form of the dependent variable allows us to interpret the results in terms of percentage changes, which enable more intuitive comparisons across different cities.

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 to announce the day-off on the previous day, day $t-1$, they can only make decisions based on the weather forecast on day $t-1$. Therefore, we 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, and no avoidance behavior is observed.

We 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, we include national holiday $nholiday_t$ 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 $doff_t$ 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. We 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.

$$\begin{aligned}\log(PS_t) = \alpha_1 \log(PS_{t-1}) + \alpha_2 \log(PS_{t-2}) + \beta_1 doff_t \\ + [\gamma_1 wind_{t-1} + \gamma_2 route_{t-1} + \gamma_3 wind_{t-1} \cdot route_{t-1} + \phi_1 rain_{t-1}] \\ + [\phi_2 rain_t + \phi_3 wind_t] + \rho_1 nholiday_t + \rho_2 DOW + \rho_3 MOY + \epsilon_t\end{aligned} \tag{2}$$

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) and (4) we estimate the effects of rainfall and wind from both Taipei City (subscript Tai) and New Taipei City (subscript $NTai$).

$$\begin{aligned}\log(PS_t) = \alpha_1 \log(PS_{t-1}) + \alpha_2 \log(PS_{t-2}) + \beta_1 doff_t \\ + \big[\gamma_1 wind_{t-1} + \gamma_2 route_{t-1} + \gamma_3 wind_{t-1} \times route_{t-1} + \phi_1 rain_{Tai,t-1} \\ + \phi_2 rain_{NTai,t-1}\big] + \rho_1 nholiday_t + \rho_2 DOW + \rho_3 MOY + \epsilon_t\end{aligned} \tag{3}$$

$$\begin{aligned}\log(PS_t) = \alpha_1 \log(PS_{t-1}) + \alpha_2 \log(PS_{t-2}) + \beta_1 doff_t \\ + \big[\gamma_1 wind_{t-1} + \gamma_2 route_{t-1} + \gamma_3 wind_{t-1} \times route_{t-1} + \phi_1 rain_{Tai,t-1} \\ + \phi_2 rain_{NTai,t-1}\big] + \big[\phi_3 rain_{Tai,t} + \phi_4 rain_{NTai,t} + \phi_5 wind_{Tai,t} + \phi_6 wind_{NTai,t}\big] \\ + \rho_1 nholiday_t + \rho_2 DOW + \rho_3 MOY + \epsilon_t\end{aligned} \tag{4}$$

Next, we 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. We examined different lag periods for alarms$_T$, where T includes contemporaneous (t) and one- and two-period lags ($t-1$ and $t-2$).

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

As briefly discussed in section 3, we 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 (6), (7), and (8). $Hurricane\_Watch_(t-2)$ is the hurricane alarm people receive where we use two lag periods because the announcement occurs 48 hours in advance. Similarly, $Hurricane_Warning_(t-1)$is the hurricane alarm people receive, where we 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.

$$\begin{aligned}\log(PS_t) = {} & \alpha_1 \log(PS_{t-1}) + \alpha_2 \log(PS_{t-2}) + \beta_1 \text{Hurricane\_Watch}_{t-2} \\ & + \rho_1 \text{DOW} + \rho_2 \text{MOY} + \epsilon_t\end{aligned} \tag{6}$$

$$\begin{aligned}\log(PS_t) = {} & \alpha_1 \log(PS_{t-1}) + \alpha_2 \log(PS_{t-2}) + \beta_1 \text{Hurricane\_Watch}_{t-2} \\ & + \gamma_1 \text{wind}_t + \gamma_2 \text{rain}_t + \rho_1 \text{DOW} + \rho_2 \text{MOY} + \epsilon_t\end{aligned} \tag{7}$$

$$\begin{aligned}\log(PS_t) = {} & \alpha_1 \log(PS_{t-1}) + \alpha_2 \log(PS_{t-2}) + \beta_1 \text{Hurricane\_Watch}_{t-2} \\ & + \beta_2 \text{Hurricane\_Warning}_{t-1} + \gamma_1 wind_t + \gamma_2 rain_t \\ & + \rho_1 DOW + \rho_2 MOY + \epsilon_t\end{aligned} \tag{8}$$

5. RESULTS

5.1. Avoidance behavior

Table 4 presents the regression estimates of 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 72.2% and 81.0% and are significant at the 1% level, respectively. In specifications (2) and (4), people also respond to day-off orders, and there are 56.9% and 72.5% 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.

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 26% increase in passenger trips on holidays. However, in Taipei and New Taipei, fewer people use the metro system during holiday periods, with around a 30% 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 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 Taiwan passenger rides are also reduced by around 10% when people receive alarms. One important

Table 4: Estimated Impacts of Day-off Order on number of passengers (fixed-effects)

	Kaohsiung		Taipei	
Specification	**(1)**	**(2)**	**(3)**	**(4)**
ln(PS$_{t-1}$)	0.361***	0.350***	0.147***	0.166***
	(0.015)	(0.015)	(0.012)	(0.012)
ln(PS$_{t-2}$)	-0.077***	-0.065***	0.0007	-0.003***
	(0.013)	(0.013)	(0.012)	(0.012)
doff$_t$	-0.722***	-0.569***	-0.810***	-0.725***
	(0.027)	(0.029)	(0.022)	(0.022)
rain$_{t-1}$	0.0005***	0.0008***	0.0002***	0.0003***
	(0.00009)	(0.00009)	(0.00008)	(0.00008)
wind$_{t-1}$	-0.0009*	-0.0007	0.001***	0.001***
	(0.0005)	(0.0005)	(0.0003)	(0.0003)
Kaohsiung rain$_t$		-0.001***		
		(0.00009)		
Kaohsiung wind$_t$		-0.012***		
		(0.003)		
Taipei rain$_t$			-0.001***	
			(0.0001)	
Taipei wind$_t$			0.008***	
			(0.003)	
New Taipei rain$_t$				-0.00006
				(0.0001)
New Taipei wind$_t$				-0.015***
				(0.003)
Nhday	0.257***	0.258***	-0.299***	-0.296***
	(0.012)	(0.011)	(0.008)	(0.007)
R-squared	0.805	0.816	0.871	0.880

Notes: Enclosed in the ( ) reports a standard error. The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

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, we 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.

We use transportation data to proxy people's avoidance behavior, and the results pre-

Table 5: Avoidance Behavior: Miami Dade County Metrobus System (Fixed-effects)

Specification	(5a)	(5b)	(5c)	(5d)
ln(busride$_{t-1}$)	0.452***	0.455***	0.472***	0.455***
	(0.035)	(0.036)	(0.035)	(0.036)
ln(busride$_{t-2}$)	-0.024	-0.037	-0.049	-0.047
	(0.030)	(0.030)	(0.031)	(0.030)
Average wind speed	-0.006***	-0.007***	-0.008***	-0.007**
	(0.001)	(0.001)	(0.001)	(0.001)
Rain	-0.071***	-0.072***	-0.071***	-0.071***
	(0.009)	(0.009)	(0.009)	(0.009)
Alarm$_t$	-0.302***			
	(0.036)			
Alarm$_{t-1}$		-0.269***		-0.182***
		(0.038)		(0.046)
Alarm$_{t-2}$			-0.257***	-0.154***
			(0.038)	(0.046)
R-squared	0.779	0.777	0.776	0.778

Notes: Enclosed in the ( ) reports a standard error. The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

sented in Tables 4 and 5 provide evidence of avoidance behavior. However, we 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, we 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 announce a day-off order with moderate and severe typhoons. Therefore, we select similar magnitude tropical storms in Miami, which are storms categorized as hurricanes. We test the specification to examine responses to 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.

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

Table 6: Avoidance Behavior: Miami-Dade County Bus System with Different Warning Types (Fixed-effects)

Specification	(6)	(7)	(8)
$\ln(\text{busride}_{t-1})$	0.398***	0.386***	0.377***
	(0.035)	(0.034)	(0.034)
$\ln(\text{busride}_{t-2})$	-0.061**	-0.055*	-0.049*
	(0.030)	(0.029)	(0.029)
Average wind speed		-0.006***	-0.005***
		(0.001)	(0.001)
Rain		-0.069***	-0.069***
		(0.009)	(0.009)
Hwatch_{t-2}	-0.730***	-0.707***	-0.425***
	(0.047)	(0.047)	(0.050)
Hwarning_{t-1}			-0.245***
			(0.039)
R-squared	0.789	0.796	0.805

Notes: Enclosed in the parentheses are the standard errors. The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

6. 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(Field et al., 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 on action for the public to make avoidance decisions. We 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 indicates that there is a 55% to 81% drop in metro passenger trips when day-off orders are announced, respectively. 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.

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

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, we 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 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 provided information, those who are unaware or have less experience may fail to take action 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, we 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.

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APPENDIX

Table A1: Avoidance Behavior: Miami-Dade County Metrobus System (Time Trend)

Specification	(5a)	(5b)	(5c)	(5d)
ln(busride$_{t-1}$)	0.392*** (0.031)	0.394*** (0.031)	0.398*** (0.031)	0.394*** (0.031)
ln(busride$_{t-2}$)	-0.393*** (0.024)	-0.393*** (0.024)	-0.393*** (0.024)	-0.395*** (0.024)
Awind	-0.006** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)
Rain	-0.087*** (0.016)	-0.089*** (0.016)	-0.088*** (0.016)	-0.088*** (0.016)
Alarm	-0.317*** (0.060)	-0.285*** (0.062)	-0.201** (0.078)	-0.260*** (0.062)
DOW	-0.012** (0.005)	-0.012** (0.005)	0.011** (0.005)	0.012*** (0.012)
MOY	-0.008*** (0.0005)	-0.008*** (0.0005)	-0.008*** (0.0005)	-0.008*** (0.0005)
R-squared	0.311	0.309	0.308	0.310

Notes: Enclosed in the ( ) reports a standard error. The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

Table A2: Avoidance Behavior: Miami-Dade County Metrorail System (Time Trend)

Specification	(5a)	(5b)	(5c)	(5d)
ln(metroride$_{t-1}$)	0.539*** (0.031)	0.541*** (0.031)	0.544*** (0.031)	0.541*** (0.031)
ln(metroride$_{t-2}$)	-0.436*** (0.024)	-0.435*** (0.024)	-0.435*** (0.024)	-0.436*** (0.024)
Awind	-0.006 (0.003)	-0.006* (0.003)	-0.007* (0.003)	-0.006* (0.003)
Rain	-0.064*** (0.022)	-0.067*** (0.022)	-0.066*** (0.022)	-0.066*** (0.022)
Alarm	-0.305*** (0.078)	-0.238*** (0.081)	-0.169* (0.102)	-0.216*** (0.081)
DOW	-0.017** (0.008)	-0.017** (0.008)	-0.018** (0.008)	-0.018** (0.008)
MOY	-0.004*** (0.0007)	-0.004*** (0.0007)	-0.004*** (0.0007)	-0.004*** (0.0007)
R-squared	0.307	0.304	0.304	0.305

Notes: Enclosed in the ( ) reports a standard error. The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.

Table A3: Avoidance Behavior: Miami-Dade County Metromover System (Time Trend)

Specification	(5a)	(5b)	(5c)	(5d)
ln(moverride$_{t-1}$)	0.319*** (0.028)	0.320*** (0.028)	0.321*** (0.028)	0.320*** (0.028)
ln(moverride$_{t-2}$)	-0.029 (0.026)	-0.029 (0.026)	-0.029 (0.026)	-0.030 (0.026)
Awind	-0.006 (0.004)	-0.007 (0.004)	-0.007* (0.004)	-0.007 (0.004)
Rain	-0.066** (0.025)	-0.067*** (0.025)	-0.067*** (0.025)	-0.067*** (0.025)
Alarm	-0.231** (0.094)	-0.198** (0.096)	-0.150 (0.121)	-0.166* (0.094)
DOW	0.015** (0.006)	0.015** (0.006)	0.015** (0.006)	0.015** (0.006)
MOY	-0.003*** (0.0008)	-0.003*** (0.0008)	-0.003*** (0.0008)	-0.003*** (0.0008)
R-squared	0.126	0.125	0.124	0.125

Notes: Enclosed in the ( ) reports a standard error. The 1%, 5%, and 10% levels of significance are given as ***, **, and *, respectively.